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BRG REVIEW

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From the Desk of the Editor

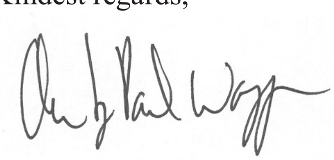
Welcome to the third edition of Berkeley Research Group Review ("the Review"), the official publication of Berkeley Research Group, LLC ("BRG"). BRG was founded in 2010 by a group of distinguished academics and private sector professionals in the fields of economics, finance, health care, and data analytics. BRG engages primarily, but not exclusively, in litigation consulting—providing innovative solutions and analyses to the complex problems being addressed in the courts today.

Our first paper presents a novel metric, organizational research quotient ("RQ"), which can help firms determine the best ways to extract value from innovation (i.e., by obtaining a patent, maintaining secrecy, leveraging complementary assets, or being the first mover/entrant in a market). This paper draws on years of research conducted by BRG Director and Washington University of St. Louis Professor Anne Marie Knott, who recently published "The Trillion-Dollar R&D Fix" in the Harvard Business Review. Dr. Knott is already implementing this research for BRG clients.

The second paper presents a financial economics-based approach to determining how efficient the market for a particular stock is. The market for a stock is said to be "semistrong form efficient" if the observed stock price incorporates all publicly available information. The extent of efficiency of the market for a stock has important implications in securities litigation, especially at the class certification stage, and the paper details these applications. As a negative proxy for market efficiency, this paper utilizes arbitrage risk, which is the primary cost incurred in making a market efficient. Because of the nature of the material covered, this paper is somewhat technical. The concepts, methods, and empirical findings are broadly discussed in the introduction and explained later in the paper.

As always, we hope to use the Review to provide our audience with a "good read" and reinforce our connections with clients, recruits, peers, and colleagues. We expect that the Review will stimulate discussion and debate around key issues we face today. With this in mind, we welcome any comments or feedback you have about the subjects we raise in the Review.

Kindest regards,



C. Paul Wazzan, Ph.D.
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Dr. Knott has published numerous articles on innovation and entrepreneurship in *Management Science, Organization Science, Strategic Management Journal*, and *Research and Technology Management*. In addition she authored the text "Venture Design," now in its second edition.

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The Performance Effects of R&D Appropriation Methods

Abstract

There are various ways to appropriate the returns to innovation, including obtaining patents, maintaining secrecy, leveraging complementary assets, and being the first mover/entrant in a market. Firms wrestle with which mechanism to employ for any given innovation. No reliable measures have existed for determining which mechanism is most effective. A new measure, organizational research quotient (RQ), solves that problem. We first review the literature on appropriation methods. We then examine the correlation between RQ and patents at the firm and find (both at the firm and industry level and using patent and survey data) that R&D effectiveness (RQ) decreases with patent intensity.

I. Introduction

One of the most important considerations for firms that innovate is how best to appropriate the returns from that innovation. This consideration takes two forms: first, how to extract the greatest returns from the innovation assuming the firm is a monopolist (i.e., what set of markets, products, distribution systems, and advertising optimize profits from the innovation); second, how to ensure that the firm rather than its rivals captures these returns (i.e., how to protect intellectual property rights).

There are various ways to appropriate the returns to innovation, including obtaining patents, maintaining secrecy, leveraging complementary assets, and being the first mover/entrant in the market. Firms wrestle with which of these mechanisms to employ for any given innovation. The reason they struggle is that there have been no reliable measures for determining which mechanism is most effective. A new measure, organizational research quotient (RQ), solves that problem.

II. Appropriation Methods

In this section, we briefly describe some of the main points regarding each of the primary methods of appropriating the returns from innovation.

A. Patents

A patent is a grant made by a government that confers upon the creator of an invention the sole right to make, use, and sell that invention for a set period of time. The goal of patent law is to stimulate innovation by granting intellectual property rights while simultaneously diffusing the knowledge underlying the invention by requiring full disclosure. The patent application generally contains the background and a description of the invention, along with visual materials such as drawings, plans, or diagrams to better describe the invention.[1] Patents are commonly used to commercialize innovations, defend an incumbent against potential lawsuits, license a technology to other firms, or block another firm's patents.

Patents have a number of drawbacks. The first drawback is the requirement to fully disclose the invention, because the disclosure can release valuable information to competitors on potentially profitable research areas or means to invent around the patent. Even if rivals can't invent around the patent, they have full rights to replicate the invention once the patent expires. The most notable example of this problem occurs in the pharmaceutical industry. Generic drug manufacturers exist precisely because large pharmaceutical firms must disclose complete information in each patent application.[2]

Another drawback of patents is that they are costly to file, maintain, and defend. It costs approximately \$10,000 to \$30,000 in legal and filing fees to obtain a patent.[3] Firms must also pay renewal fees 3 1/2, 7 1/2, and 11 1/2 years following the granting of the patent. If the firm plans to market and protect the invention outside the United States, it needs to file (and incur fees comparable to those in the United States) in other countries. Finally, approximately 1.5 percent of patents are the subject of litigation.[4] A 2009 survey conducted by the American Intellectual Property Law Association indicated that the average cost to litigate patent infringement cases with less than \$1 million at risk was approximately \$1 million, while the cost to litigate cases with greater than \$25 million at risk was approximately \$6.3 million.[5]

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[1] One recent change to the patent process is worth noting. On September 16, 2011, President Obama signed into law the Leahy-Smith America Invents Act. Among other changes, the act implements a first-inventor-to-file standard for patent approval for applications filed on or after March 16, 2013.

[2] A new legal development that further favors generics over branded pharmaceutical firms is that generics are immune from liability lawsuits because they make no claims of the drug's efficacy. Thus, generics free-ride not only on branded pharmaceuticals' technology, but also on their efficacy claims. (Katie Thomas, "Generic Drugs Proving Resistant to Damage Suits," *New York Times*, March 20, 2012.)

[3] Mark A. Lemley, "Rational Ignorance at the Patent Office," 95 *Northwestern University Law Review* 1495 (2001).

[4] Mark A. Lemley and Carl Shapiro, "Probabilistic Patents," 19 *Journal of Economic Perspectives* 75 (2005).

[5] American Intellectual Property Law Association, *Report of the Economic Survey* (2009).

Finally, effective patent enforcement requires active monitoring of potential infringement and the resources to pursue legal action if infringement is detected. For inventions that are easy to invent around or need to survive beyond the 20-year patent life, or for firms with limited economic resources, patents are infeasible. In these cases, firms must resort to other appropriation mechanisms.

B. Trade Secrets

One of the most important alternatives to patenting is to maintain trade secrets. In contrast to patents, secrecy can potentially protect the invention indefinitely. Under the Uniform Trade Secrets Act (UTSA), a trade secret is defined as information including a formula, pattern, compilation, program, device, method, technique, or process that: (i) derives independent economic value, actual or potential, from not being generally known to, and not being readily ascertainable by proper means by, other persons who can obtain economic value from its disclosure or use; and (ii) is the subject of efforts that are reasonable under the circumstances to maintain its secrecy.[6]

The most notable example of a trade secret is the formula for Coca Cola, which has been kept secret since its creation in 1886. The company takes extraordinary measures to maintain the secret. For example, the formula for Coke is kept in an Atlanta bank vault that can be opened only by board resolution. In addition, only two employees (whose identities are kept secret) know the formula at any time. Those two employees are not allowed to be on a flight together.

While secrecy can protect work in progress as well as a range of inventions broader than patents, it comes with its own set of drawbacks. First is the inherent difficulty to protect secrets—technical knowledge is carried by individuals, and if the secret is more complex than the formula for Coke, it is difficult to define what employees can say or not say in conjunction with the secret. Thus, the secret may be divulged unintentionally. Second, if an organization wants to maintain trade secrets, it typically can't engage in cooperative R&D involving the trade secret. Thus, firms that strongly focus on internal information sources could give greater emphasis to secrecy, while firms that extensively use cooperative R&D requiring the sharing of valuable information could find patents of greater value.

[6] UTSA section 1.4.

C. Complementary Assets

A number of studies emphasize the importance of complementary assets in appropriating the returns to innovation. David Teece describes the nature of complementary assets as follows: "In almost all cases, the successful commercialization of an innovation requires that the know-how in question be utilized in conjunction with other capabilities or assets. Services such as marketing, competitive manufacturing, and after-sales support are almost always needed. These services are often obtained from complementary assets which are specialized."[7] For example, the commercialization of a new drug is likely to require the dissemination of information over a particular information channel. Commercialization may also require large-scale and high-quality manufacturing capabilities so that the innovator is in a position to satisfy a large surge in consumer demand, while maintaining product quality. A research firm that lacks the complementary assets required to commercialize an innovation can enter into alliances, for example, to gain access to downstream distribution and after-sales service. However, alliances often enable one partner to learn more than the other, and capabilities may be transferred.

The commercialization of the computer tomography (CT) scanner provides an example in which the innovator, Electrical Musical Instruments (EMI), lost to the imitator, GE Medical Systems. Although GE did not invent the CT scanner, it quickly became the market leader because it possessed the required complementary assets, in particular large-scale manufacturing capability, a knowledgeable distribution network, and a strong maintenance force.[8] On a broader scale, Levinthal and Posen indicated that the value of a blockbuster drug depends heavily on complementary assets in marketing and technical capability.[9] According to their results, the expected value of a blockbuster drug to firms in the bottom quartile of marketing and technical capability is $125 million, while the value to firms in the top 5 percent is $2 billion.

[7] David J. Teece, "Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing and Public Policy," 15 *Research Policy* 285, 288 (1985).

[8] For additional reading, see Christopher A. Bartlett, "EMI and the CT Scanner [A]," Harvard Business Case 383-194 (2001); and Christopher A. Bartlett, "EMI and the CT Scanner [B]," Harvard Business Case 383-195 (1985).

[9] Daniel A. Levinthal and Hart E. Posen, "Myopia of Selection: Does Organizational Adaptation Limit the Efficacy of Population Selection?" 52 *Administrative Science Quarterly* 586 (2007).

D. First-Mover Advantages

The significance of first-mover advantages or speed to market is the subject of extensive research.[10] Marvin Lieberman and David Montgomery identify three primary sources of first-mover advantages: technological leadership, preemption of scarce assets, and buyer switching costs.[11] *Technological leadership* includes learning effects, in which a firm's unit costs decline with cumulative production[12]; and success in patent or R&D races, where advances in product or process technology are a function of R&D expenditures. *Preempting* competitors in the acquisition of scarce assets leaves them with lower-quality assets with either lower demand or higher cost. Examples of scarce assets include input factors such as natural resources, prime retailing and manufacturing locations, and labor. *Switching costs* exist when the cost to try a new product is higher than the cost to retain an existing product. When switching costs are present, later entrants must invest additional resources to attract customers away from the first mover. A notable example of switching costs pertains to experience goods. An experience good is one in which the customer can't assess product quality in advance. When such information asymmetries are present, buyers may rationally stick with the first brand they encounter that satisfactorily performs the job. As a result, investments to establish the brand name may outlive the patent itself.

A final example of first-mover advantage is one not considered by Lieberman and Montgomery, perhaps because it has only recently gained prominence with the widespread adoption of Internet-based applications—*network externalities*. Network externalities exist when the value of a product/service increases with the number of other people using that product/service (the network). A salient example is eBay, which is successful not because it patented its C2C platform, but because it enjoys a virtuous cycle: a site with more sellers attracts more buyers, and a site with more buyers attracts more sellers. Thus the first mover (unless it makes tragic mistakes) is likely to have the highest number of buyers and sellers.

[10] For a summary, see Marvin B. Lieberman and David B. Montgomery, "First-Mover (Dis)advantages: Retrospective and Link with the Resource-Based View," 19 *Strategic Management Journal* 1111 (1998).

[11] Marvin B. Lieberman and David B. Montgomery, "First-Mover Advantages," 9 *Strategic Management Journal* 41 (1988).

[12] Learning effects often arise from engineering changes and workforce training. For a discussion of the complex process that gives rise to learning effects, see Paul S. Adler and Kim B. Clark, "Behind the Learning Curve: A Sketch of the Learning Process," 37 *Management Science* 267 (1991).

E. Summary of Appropriation Methods

The availability, use, and effectiveness of the various appropriation methods differ across industries, firms within an industry, and inventions within a firm. Moreover, the four appropriation methods are not mutually exclusive. (The survey results discussed below confirm this point.) For example, a firm could use secrecy to protect an invention during a development phase and then rely on other appropriation methods when the invention is on the market. Similarly, a company with large-scale manufacturing can ride down the learning curve more quickly and reach a low-cost position not attainable by competitors without such capabilities. Thus there are a number of mechanisms for appropriation. At issue is which is most effective under a given set of circumstances.

III. Trends in Patenting

In this section, we discuss trends in patenting because they are widely believed to be the primary means of appropriating the returns to innovation.[13] This belief partially stems from the fact that among the appropriation mechanisms, only trends are under the control of policymakers. Thus when policymakers want to influence the level of innovation, patent reform is one of the primary means to accomplish that. For example, the headline for the White House press release accompanying President Obama's recent signing of the Leahy-Smith America Invents Act read: "President Obama Signs America Invents Act, Overhauling the Patent System to Stimulate Economic Growth." Moreover, management has become increasingly preoccupied with patenting in recent years.[14]

Figure 1 plots the total utility patents the U.S. Patent and Trademark Office issued from 1970 to 2010.[15] The large increase is consistent with the notion that obtaining patents is one of the most important means of appropriating the returns to innovation. In the remainder of this section, we briefly review some of the key changes that have taken place in the U.S. patent system since 1980. [16]

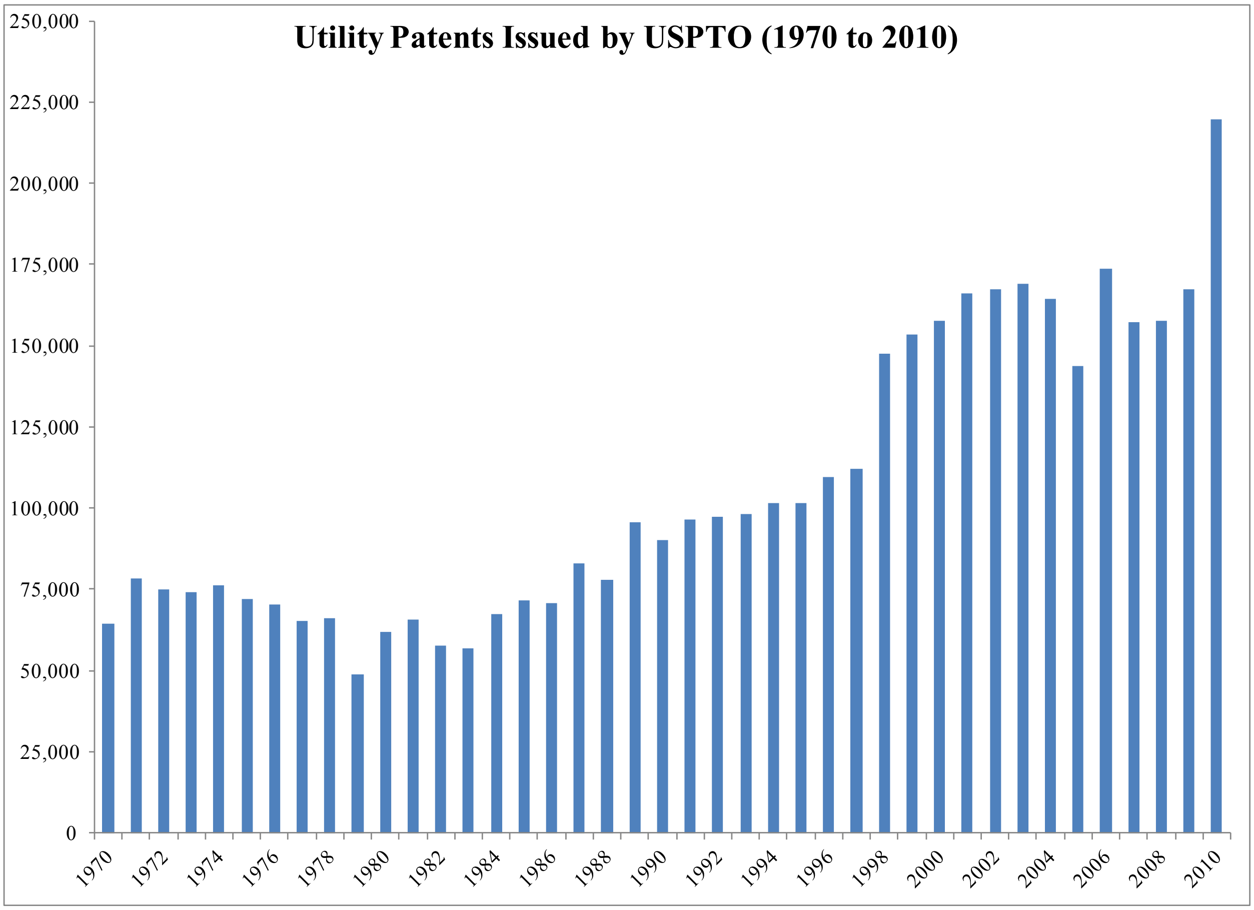
[13] This is despite the fact that less than 40 percent of firms doing R&D file patents in any given year.

[14] See, e.g., Kevin G. Rivette and David Kline, "Discovering New Value in Intellectual Property," 78 *Harvard Business Review* 54 (2000).

[15] Utility patents are also referred to as "patents for invention" and are issued for the invention of a new and useful process, machine, manufacture, or composition of matter, or a new and useful improvement thereof.

[16] This section is meant as an introduction to this complex topic. For more detailed readings, see Adam B. Jaffe, "The U.S. Patent System in Transition: Policy Innovation and the Innovation Process," 29 *Research Policy* 531 (2000); and Nancy T. Gallini, "The Economics of Patents: Lessons from Recent U.S. Patent Reform," 16 *Journal of Economic Perspectives* 131 (2002).

Figure 1



The Bayh-Dole Act (or Patent and Trademark Law Amendments Act) of 1980 instituted a uniform federal patent policy for universities and small businesses under which they obtained the rights to patents resulting from grants or contracts funded by any federal agency. In the wake of Bayh-Dole, an increasing number of universities became directly involved in patenting and licensing.[17] Although this trend had begun well before passage of Bayh-Dole, Bhaven Sampat writes that the act endorsed "universities' involvement in patenting and licensing" and "assuaged remaining fears on the part of university administrators and faculty researchers about the adverse reputational consequences of involvement in the 'business-side' of patenting and licensing."[18]

[17] For an analysis of the significance of the increased university patenting, see David C. Mowery and Arvids A. Ziedonis, "Numbers, Quality, and Entry: How Has the Bayh-Dole Act Affected U.S. University Patenting and Licensing," 1 *Innovation Policy and the Economy* 187 (2000).

[18] Bhaven N. Sampat, "Patenting and US Academic Research in the 20th century: The World Before and After Bayh-Dole," 35 *Research Policy* 772, 780 (2006).

Another major change occurred in 1982, when the U.S. Congress established the Court of Appeals for the Federal Circuit (CAFC). Before 1982, appeals of patent cases were heard in the various appellate circuit courts. The circuit courts differed considerably in their interpretation of patent law, with some more than twice as likely as others to uphold patent claims. In addition, the U.S. Supreme Court rarely heard patent-related cases.

Most commentators agree that the creation of the CAFC has made it easier to secure patents, enforce patents against others, and receive large financial awards from such enforcement. Creation of the CAFC has also made it harder for those accused of infringing patents to challenge the patents' validity. The increase in protection by the courts led to an increase in firms applying for patents, because firms knew their intellectual property rights would be protected. For example, Adam Jaffe and Josh Lerner write: "A comparison of the CAFC's rulings with those of the previous courts illustrates the magnitude of the change. Whereas the circuit courts had affirmed 62 percent of district-court findings of patent infringement in the three decades before the creation of the CAFC, the CAFC in its first eight years affirmed 90 percent of such decisions."[19] In addition, rulings at the district court level were affected. Jaffe and Lerner further write: "Prior to the creation of the CAFC, about 30 percent of the patents were found to be valid and infringed at the district court level. After the creation of the CAFC, the percentage of awards upheld rose to over 55 percent."[20]

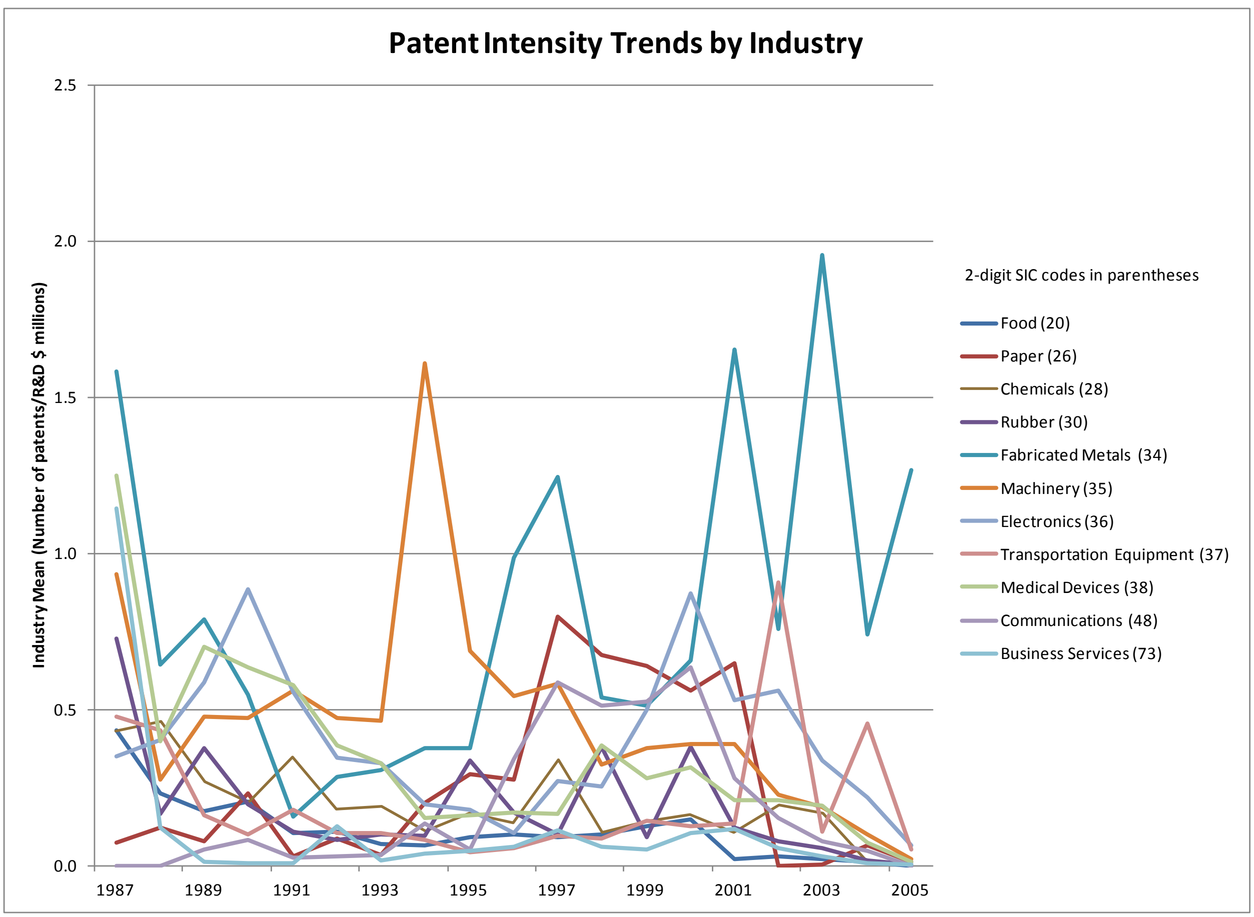
During the early 1980s, two opinions by the Supreme Court broadened the definition of patentable subject matter. *Diamond v. Chakrabarty* concerned a microbiologist's invention of human-made, genetically engineered bacteria capable of breaking down multiple components of crude oil, a capability possessed by no naturally occurring bacteria.[21] The Court held that "Committee Reports accompanying the 1952 Act inform us that Congress intended statutory subject matter to 'include anything under the sun that is made by man.'"[22] And in *Diamond v. Diehr*, the Court held that a "claim drawn to subject matter otherwise statutory does not become non-statutory simply because it uses a mathematical formula, computer program, or digital computer."[23] At issue in this case was a process for curing synthetic rubber that employed a mathematical formula and a programmed digital computer. Recently, opinions by the Court have restricted the rights of patent holders. For example, in *KSR International*

[19] Adam B. Jaffe and Josh Lerner, *Innovation and Its Discontents* 104, Princeton University Press (2004).
[20] *Id.*
[21] 447 U.S. 303 (1980).
[22] 447 U.S. 303, 309 (1980).
[23] 450 U.S. 175, 187 (1981).

Co. v. Teleflex Inc., the Court essentially made it more difficult for inventors to obtain patents or patent holders to enforce patents by imposing more restrictive guidelines on whether a given invention met the burden of being non-obvious.[24]

Because we lack good measures of R&D effectiveness, it is unclear whether the increased patenting reflects increased innovation or merely a higher propensity to patent innovations. One casual way to test this is to examine what has happened with patent intensity, defined as the ratio of the number of patents to R&D spending. Figure 2 shows trends in patent intensity by industry. The figure indicates that with the exception of fabricated metal products (SIC 3400), the number of patents per dollar of R&D spending has decreased over time. This suggests that the increase in patents in Figure 1 stems from increases in R&D spending and increased patenting by universities and foreign firms rather than an increased use of patents by firms.

Figure 2



[24] 548 U.S. 902 (2006).

IV. Empirical Studies of Appropriability Mechanisms

In this section, we provide a brief overview of the empirical literature on appropriability mechanisms. This abbreviated treatment is meant to highlight certain aspects of the literature. As such, it will not do justice to the complex issues involved, and we refer the interested reader to a variety of additional readings.[25]

A. Executive Surveys

Studies comparing the various methods of appropriability rely upon executive surveys because there are no direct measures for methods other than patents. Surveys permit researchers to investigate the subject indirectly and qualitatively by examining the effectiveness of the various means. The 1983 Yale survey and the 1994 Carnegie Mellon survey (CMS) present systematic evidence on the perceived effectiveness of different appropriability methods.[26] The combined results from the two surveys are summarized in Table 1 for selected manufacturing industries. Table 1 reports the percentage of firms within industries that ranked each appropriability strategy as the first or second most important method in protecting the competitive advantage from their innovations.[27]

[25] Two recent review articles are good starting points: Andrés López, "Innovation and Appropriability: Empirical Evidence and Research Agenda," in *The Economics of Intellectual Property, Suggestions for Further Research in Developing Countries and Countries with Economies in Transition*, Chapter 1 (2009); and Bronwyn Hall, Christian Helmers, Mark Rogers, and Vania Sena, *The Choice Between Formal and Informal Intellectual Property: A Literature Review* (working paper, April 2012).

[26] For the Yale survey results, see Richard C. Levin, Alvin K. Klevorick, Richard R. Nelson, and Sidney G. Winter, "Appropriating the Returns from Industrial Research and Development," 1987 *Brookings Papers on Economic Activity* 783 (1987). For the CMS results, see Wesley M. Cohen, Richard R. Nelson, and John P. Walsh, "Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (Or Not)," NBER Working Paper 7552 (2000). The results from the two surveys are not perfectly comparable. In the Yale survey, respondents were asked about the typical experiences or central tendencies within a particular industry. In the CMS, respondents were asked about which appropriability mechanisms had been effective in protecting the firm's competitive advantage from innovations.

[27] The table covers both product and process innovations. It was constructed using the original respondent-level survey data and was originally published in 18 Marco Ceccagnoli and Frank T. Rothaermel, "Appropriating the Returns from Innovation," in Gary D. Libecap and Marie C. Thursby (eds.), *Technological Innovation: Generating Economic Results, Advances in the Study of Entrepreneurship, Innovation and Economic Growth*, Chapter 1 (2008).

Table 1: Comparing the 1983 Yale and 1994 CMS Appropriability Surveys for Selected High-Tech Industries

	% Firms within Industries Ranking Appropriability Strategy as First or Second Most Important														
	Number of Observations		Patent Protection			Secrecy			Being First to Market			Complementary Assets			
	Yale	CMS	Yale	CMS	% Change	Yale	CMS	% Change	Yale	CMS	% Change	Yale	CMS	% Change	
Industrial chemicals	73	52	0.75	0.78	4%	0.59	0.98	66%	0.80	0.68	-15%	0.79	0.78	-1%	
Drugs and medicines	17	47	0.94	0.80	-15%	0.53	0.91	72%	0.71	0.71	1%	0.71	0.51	-28%	
General industrial machinery	32	18	0.47	0.78	66%	0.41	0.94	132%	0.78	0.89	14%	0.81	0.83	3%	
Computers	21	28	0.29	0.64	125%	0.43	0.79	83%	0.86	0.89	4%	0.62	0.61	-2%	
Communication equipment	17	22	0.41	0.62	50%	0.53	0.81	53%	0.88	1.00	13%	0.94	0.81	-14%	
Semiconductors	10	17	0.50	0.63	25%	0.20	0.94	369%	0.90	0.94	4%	0.70	0.75	7%	
Motor vehicles	24	27	0.63	0.76	22%	0.33	0.76	128%	0.71	0.92	30%	0.79	0.60	-24%	
Aircraft and missiles	21	41	0.38	0.54	41%	0.48	0.95	99%	1.00	0.92	-8%	0.71	0.62	-14%	
Search and navigation equipment	9	29	0.44	0.66	47%	0.67	0.97	45%	1.00	0.86	-14%	0.89	0.83	-7%	
Measuring and controlling device	18	25	0.33	0.65	96%	0.28	0.87	213%	0.94	0.96	1%	0.78	0.74	-5%	
Medical instruments	12	60	0.58	0.73	26%	0.50	0.83	67%	1.00	0.90	-10%	0.83	0.72	-14%	
Total manufacturing	650	852	0.53	0.67	28%	0.47	0.89	91%	0.84	0.87	4%	0.80	0.73	-8%	

Source: 18 Marco Ceccagnoli and Frank T. Rothaermel, Appropriating the Returns from Innovation in Technological Innovation: Generating Economic Results, Advances in the Study of Entrepreneurship, Innovation and Economic Growth, Chapter 1 (2008).

Secrecy was perceived as the most important method in the CMS, with 89 percent of the respondents ranking it as the first- or second-most important appropriability method. The CMS results also suggest that secrecy has increased in importance. The percentage of firms ranking secrecy in the top two was almost double the percentage in the Yale survey (47 percent). Patents were perceived as the least important in the CMS, even though the share of firms ranking them first or second increased from 53 percent in the Yale survey to 67 percent in the CMS. Being first to market was perceived as the second-most important factor in the CMS, with the percentage of firms ranking it in the top two increasing slightly between the Yale survey (84 percent) and the CMS (87 percent). Ownership of complementary assets was perceived as the third-most important appropriation method (of four). Although 73 percent of the firms ranked it first or second, the percentage of firms doing so was 8 percent lower than in the Yale survey (80 percent). Industry-specific figures display substantial changes across time. For example, in the semiconductor industry, only 20 percent of respondents in the Yale survey ranked secrecy first or second. Approximately 10 years later, the percentage had increased to 94 percent.

One of the recent trends affecting choice of appropriation methods is the rise in collaborative R&D. Anthony Arundel investigates the effects of inter-firm cooperation using results from the 1993 European Community Innovation Survey (ECIS) and finds weak evidence that participation in cooperative R&D ventures increases the value of patents over secrecy for product innovations.[28] Bruno Cassiman and Reinhilde Veugelers examine the ECIS results and find that cooperation with customers or suppliers reduces the effectiveness of "strategic" protection measures (i.e., secrecy, complexity, and lead time).[29] The result suggests that commercially sensitive information that firms might indirectly disseminate through cooperative agreements could have a negative effect on a firm's efforts to appropriate returns. Accordingly, it seems likely firms are only willing to engage in cooperation with patented or non-critical technology.

Aija Leiponen and Justin Byma examine the relationship between size, cooperation, and appropriation.[30] They find that cooperative activities greatly influence the choice of intellectual property strategy. Small firms tend to rely on speed to market rather than patents or secrecy. The relationship is particularly true for R&D-intensive small firms that are engaged in horizontal R&D cooperation or have vertical business dependencies (defined as a single client or supplier providing at least one-third of its business). The authors offer two possible explanations. The first is that small firms do not have the resources to originate and defend patents, and that trade secrets are difficult to maintain in close, cooperative business relationships. The second is that small firms may have limited bargaining power within external relations (assuming they are dealing with bigger firms). Therefore, most innovative small firms simply accelerate their investments to enter markets quickly.

B. Appropriability and Firm Performance

The relationship between appropriability method and firm performance has received little scrutiny for two chief reasons. First, other than patents, there are no direct measures of their use.[31] Second, there are no good measures of R&D effectiveness. A few studies, however, examine appropriability using

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[28] Anthony Arundel, "The Relative Effectiveness of Patents and Secrecy for Appropriation," 30 *Research Policy* 611 (2001).

[29] Bruno Cassiman and Reinhilde Veugelers, "R&D Cooperation and Spillovers: Some Empirical Evidence from Belgium," 92 *American Economic Review* 1169 (2002).

[30] Aija Leiponen and Justin Byma, "If You Cannot Block, You Better Run: Small Firms, Cooperative Innovation, and Appropriation Strategies," 38 *Research Policy* 1478 (2009).

[31] Several studies examine the relationship between the patents and patent citations and firm performance. See, e.g., Bronwyn H. Hall, Adam Jaffe, and Manuel Trajtenberg, "Market Value and Patent Citations," 36 *Rand Journal of Economics* 16 (2005). The authors find that an extra citation per patent increases market value by 3 percent. These studies, however, are unable to separate the impact of innovation on performance from the marginal benefits of patenting relative to alternative appropriation methods.

the executive survey data discussed in the preceding section and comparing it to top-level financial performance (rather than R&D performance).

Marco Ceccagnoli studies the relationship between appropriation method, measured using the CMS results, and firm performance, measured as the market-to-book ratio (Tobin's q).[32] Ceccagnoli finds that the strength of a firm's patent protection strategy and the ownership of specialized complementary assets are associated with a substantial increase in the stock market valuation of a firm's R&D assets relative to its tangible assets. The relationships for first-mover advantages and secrecy are not statistically significant. The lack of impact for secrecy in particular is not surprising given the difficulty financial markets would have in observing and valuing such a strategy.

Iain Cockburn and Zvi Griliches examine the relationship between appropriation methods, measured using the Yale survey results, and the market's valuation of R&D and patents.[33] Because the Yale survey questioned respondents about the typical experiences or central tendencies within a particular industry, this study only examines the relationship on an industry level. The authors find some evidence of a positive relationship between industry-level measures of patent effectiveness and the market's valuation of a firm's past R&D and patenting performance, as well as its current R&D expenditures. Cockburn and Griliches do not find any such relationship for the other appropriability mechanisms.

Ashish Arora, Marco Ceccagnoli, and Wesley Cohen use the CMS survey data to estimate the returns to patenting over and above the returns that would otherwise accrue to the underlying innovation.[34] They estimate a "patent premium," or the proportional increment to the value of an innovation realized by patenting, net of patenting costs (e.g., filing and legal expenses). The results indicate that for the U.S. manufacturing sector, the expected value of the typical innovation, if patented, is 40 percent lower than without patenting. The only exception is the medical instruments industry; in two other industries (biotech and drugs and medicines), the expected value is approximately the same whether or not the innovation is patented. However, conditional upon patenting, the expected value is almost 50 percent larger than if the innovation was not patented.

[32] Marco Ceccagnoli, "Appropriability, Preemption, and Firm Performance," 30 *Strategic Management Journal* 81 (2009).

[33] Iain Cockburn and Zvi Griliches, "Industry Effects and Appropriability Measures in the Stock Market's Valuation of R&D and Patents," 78 *American Economic Review* 419 (1988).

[34] Ashish Arora, Marco Ceccagnoli, and Wesley M. Cohen, "R&D and the Patent Premium," 26 *International Journal of Industrial Organization* 1153 (2008).

Of course, if this were true generally, all innovations would be patented, so something else is going on. Firms are making strategic decisions about (a) which innovations to protect and (b) how best to protect them. Thus firms are patenting those innovations that are best protected by patents, and accordingly, the market value for those innovations is higher when they are patented.

In summary, there is no data on what mechanisms firms actually use other than patents. (The Yale, CMS, and ECIS surveys merely ask executives what they believe is effective.) The results above regarding effectiveness presume that firms use what they believe is effective, and that there is correlation between beliefs and reality regarding the effectiveness of the appropriability mechanisms. To solve this circularity we need an independent measure of R&D effectiveness.

Our goal is to determine how the appropriability mechanisms firms use are correlated with the productivity of their R&D. We do this using a new measure of firms' R&D effectiveness: organizational research quotient.

V. Organizational Research Quotient (RQ)

A. Introduction

As mentioned previously, studies of appropriability have been hampered by lack of measures for R&D effectiveness. The primary measures—R&D spending and patent counts—have fundamental problems. The problem with R&D intensity is that it is an input measure rather than an output measure. The problem with patent counts is that patents are neither universal nor uniform (which we discuss shortly in greater detail). Finally, neither R&D spending nor patents predicts market value.[35]

The organizational research quotient (RQ) is a new measure of R&D that is universal, uniform, and reliable. Moreover, it is the most intuitive measure you can construct for R&D effectiveness. The reason it hasn't been discovered until recently is the lack of software to estimate it. As recently as five years ago, software took overnight to produce results.

[35] For more detailed readings, see Anne Marie Knott, Carl Vieregger, and James C. Yen, *IQ and the R&D Market Value Puzzle* (working paper, August 2011), available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1410853

The RQ measure is based on the production function from classic economics that defines the relationship between firm inputs and their output. The version seen in textbooks typically considers the two main tangible inputs (capital and labor) and is written as follows:

$$Y = K^{\alpha} L^{b}$$

where *Y* is output, *K* is capital, and *L* is labor. The exponents α and β, called the *output elasticity* of capital and labor, respectively, tell us in a very precise way how productive inputs are in generating output. A 1-percent increase in capital increases a firm's output α percent; a 1-percent increase in labor increases a firm's output β percent.

The RQ measure is obtained by 1) expanding the production function to include expenditures on two important intangible assets: R&D and advertising, and 2) making all the coefficients firm-specific (normally these are assumed to be common across all firms in an industry).

$$Y = K^{ai} L^{bi} R^{gi} A^{di}$$

RQ is the output elasticity of R&D investment (γ). Accordingly, it is the percentage increase in firm revenue associated with a 1-percent increase in the firm's R&D. Thus the RQ measure is simply doing with R&D what everyone has been doing for years with capital and labor.

Using the production function to characterize R&D effectiveness allows firms to understand how effective their R&D spending is on a universal scale, similar to a person's IQ. This supports comparisons to other companies as well as to the firm's own performance over time. In addition, because it measures the returns to R&D, it allows firms to compute the optimal level of R&D investment.

B. What Makes RQ a Good Measure?

There are three properties good measures should have: uniformity, universality, and reliability. *Uniformity* is the property that the measure means the same thing in all contexts; *universality* is the property that the measure can be generated for all relevant entities (in this case firms); *reliability* is the property that the measure behaves the way theory predicts it will. The easiest way to explain why these properties are important is to show how they fail for another measure. Let's use patent counts, since they are one of the most prevalent measures of R&D effectiveness.

The universality problem is that not all firms doing R&D patent their innovations. In fact, less than 40 percent of firms engaged in R&D file patents in any given year. Moreover, even among patenting firms, few patent all of their innovations. The uniformity problem is that not all patents are created equal. Compare for example the value of the patent for copying DNA versus the 97 percent of patents that are never commercialized. On average, 10 percent of patents account for 81 percent to 85 percent of the economic value of all patents. Finally, the reliability problem is that even for firms using patents, patents do not predict the outcomes that drive firms to do R&D (increased profits and market value).

One of the advantages of RQ is that it is estimated entirely from financial data. It can be defined for ANY firm doing R&D. Thus it is *universal*. In addition, RQ is unit-less (it is essentially the ratio of outputs to inputs), and thus its interpretation is *uniform* across firms regardless of country currency. Accordingly, RQs can be compared within a firm across time as well as across firms. Perhaps most important, the measure is *reliable.* Knott and colleagues find that RQ predicts both firm-level R&D investment and the stock market value of R&D![36]

C. What RQ Says About Appropriability Methods

As mentioned previously, there are two problems in assessing the effectiveness of appropriation mechanisms: the measurement problem and the problem of data on appropriability mechanisms. We have solved the measurement problem with RQ but, with the exception of patents, still have the data problem. Accordingly, we will be able to say something fairly reliable about the effectiveness of patents but will only be able to show inferential relationships for the other appropriability mechanisms.

(1) Correlation between RQ and patents at the firm level

To do our analysis of patent effectiveness, we use firm data from 2005, the last year in which patent data was linked to firm financial data. The first thing to note is that of the 423 publicly traded firms doing R&D and advertising that year, only 89 (21 percent) were granted patents in that year. Thus, in general, firms did not patent their inventions.

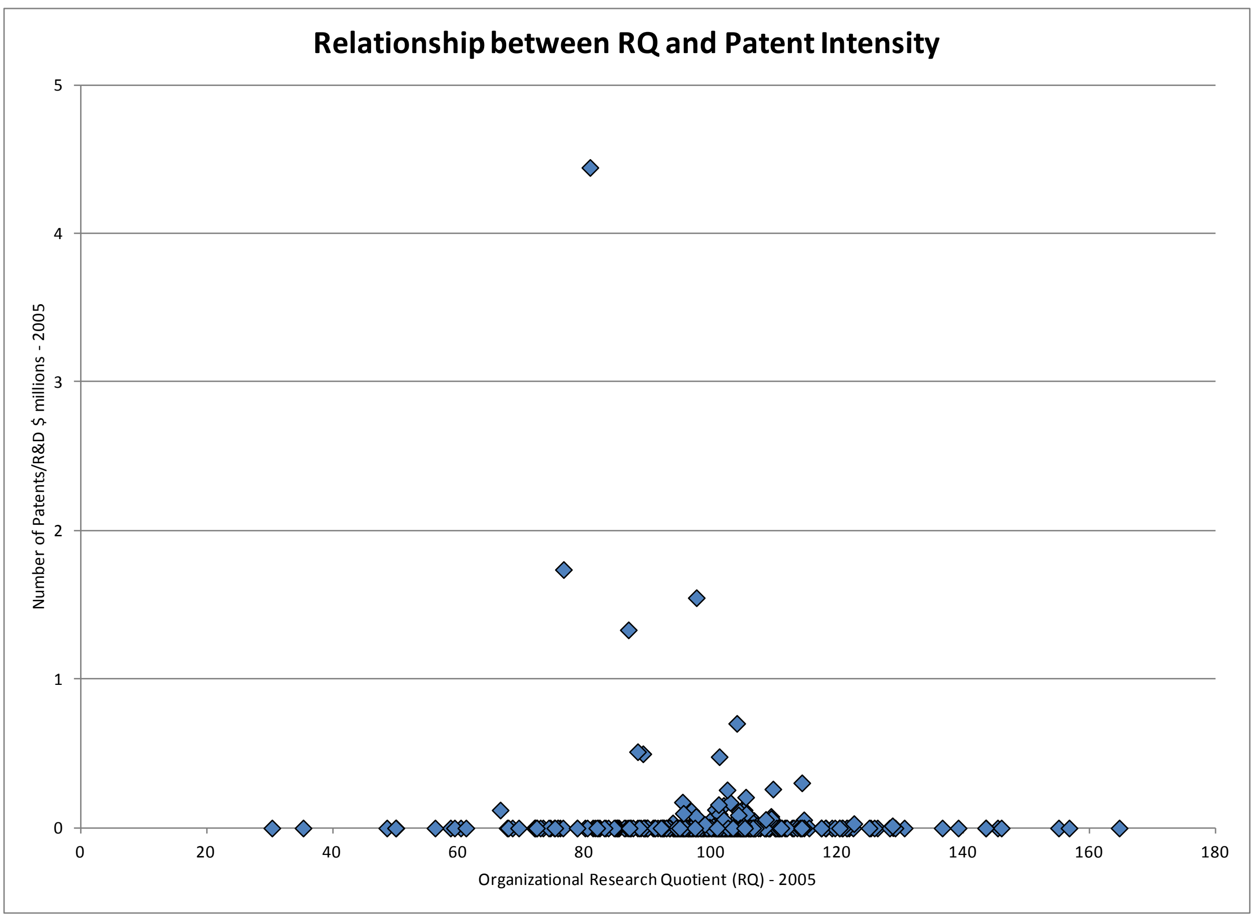
We analyze patent effectiveness by examining patent intensity (patents/R&D spending). Patent intensity is preferred over the raw number of patents because it captures the likelihood of patenting any given innovation. Figure 3 plots patent intensity versus firm RQ. The figure confirms that the bulk of

[36] For more detailed readings, see Anne Marie Knott, Carl Vieregger, and James C. Yen, *IQ and the R&D Market Value Puzzle* (working paper, August 2011), available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1410853

firms have no patents, but it also reveals that the tendency to avoid patents is distributed uniformly across R&D effectiveness. More important, the figure indicates that firms with the highest propensity to patent have low R&D capability (an RQ of 80 is in the bottom 20 percent). Thereafter the propensity to patent decreases with RQ.

While we don't know for certain what accounts for this pattern, one interpretation is that inferior firms patent to signal they have technology, but firms with superior capability are known to be superior, and therefore only patent when it makes sense strategically. Regardless of the underlying mechanism, it is clear that patenting does not increase a firm's R&D effectiveness. Firms that do the greatest amount of patenting do not have high RQs.

Figure 3



(2) Correlation between RQ and other appropriation mechanisms

To examine the effectiveness of other appropriation mechanisms, we rely on data from the CMS study discussed previously. Because the CMS researchers are bound by confidentiality agreements that preclude release of firm-level data, we utilize the industry summaries from Table 1 of Cohen, Nelson, and Walsh.[37]

Figures 4a through 4f plot each of six mechanisms against raw RQ. The six mechanisms are secrecy, patents, other legal mechanisms, lead time, complementary sales, and complementary manufacturing. The y axis in each figure is the mean percentage of product innovations for which a given mechanism is considered effective. In addition to the graphical summaries, we derived the correlation coefficient between RQ and each mechanism. What the figures and formal statistics show is that for three of the mechanisms (other legal, complementary sales, and complementary manufacturing), there is no correlation between RQ and the mechanism. RQ is positively correlated with lead time and weakly correlated with secrecy. The strongest correlation with RQ is the negative correlation with patents. (The coefficients for patents and lead time are statistically significant at the 95-percent level in a regression with all six mechanisms.) Because these data are summarized at the industry level, the way to interpret the results is that industries with high reliance on patents have lower returns to R&D, whereas industries with high reliance on lead time, and to a lesser extent secrecy, have higher returns to R&D.

[37] Wesley M. Cohen, Richard R. Nelson, and John P. Walsh, "Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (Or Not)," NBER Working Paper 7552 (2000).

Figure 4A

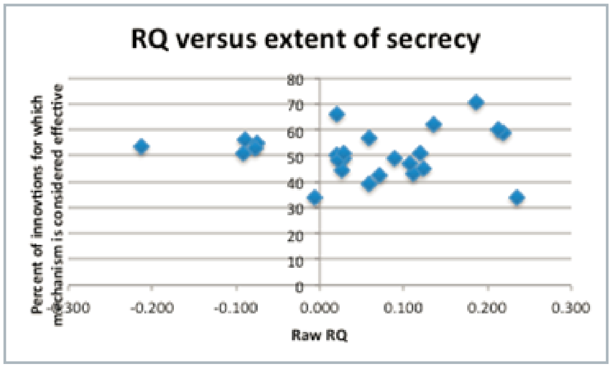


Figure 4B

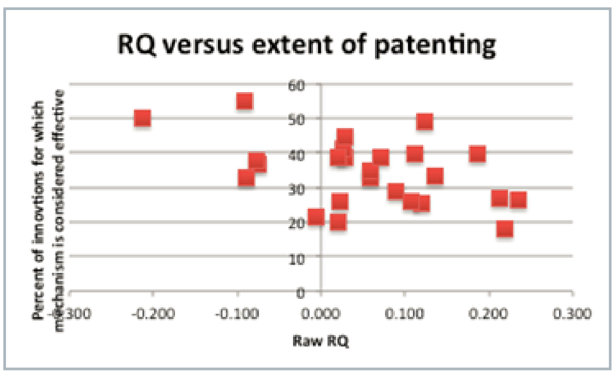


Figure 4C

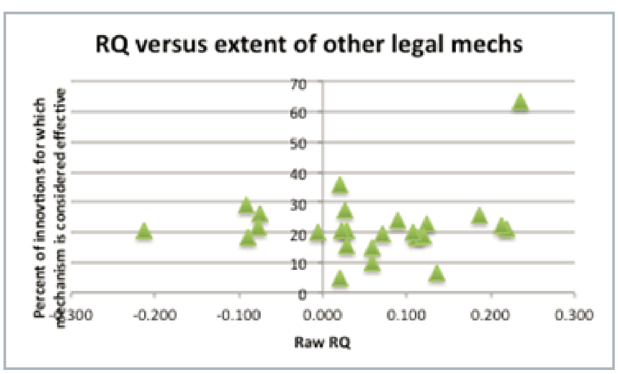


Figure 4D

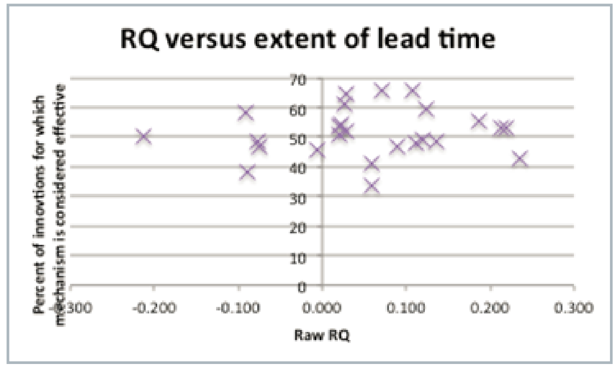


Figure 4E

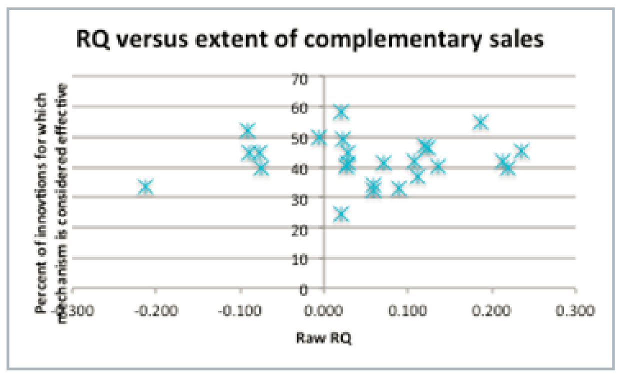
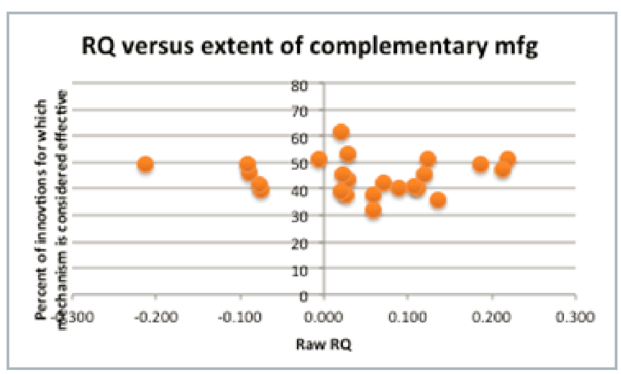


Figure 4F



VI. Conclusion

Firms struggle with many of their R&D decisions—what to spend, how to spend it, and how best to appropriate the returns from that spending. Until now, we have had very little guidance on whether their appropriability strategies are effective. RQ helps solve that problem.

Our strongest finding (both at the firm and industry level and using patent data as well as survey data) is that R&D effectiveness (RQ) decreases with patent intensity. This can be interpreted to mean both that patenting does not increase the returns to R&D and that the more effective firms are less likely to patent.

The latter interpretation is reinforced to some extent by the industry-level results showing that industries with the highest returns to R&D are more likely to view secrecy and lead time as effective means to appropriate the returns to innovation. The results for other appropriability mechanisms should be considered preliminary since they are measured at the industry level (the variance in RQ is higher within than across industry). However, because the negative patent result is so strong, it is clear smart firms use alternative appropriation mechanisms.

The results we have shown provide general indications regarding which appropriation mechanisms are collated with higher returns to R&D across a broad range of industries. These say very little about the best intellectual property policy firms. What they do a better job of highlighting is that intellectual property policy (as well as most other components of innovation strategy) has a tremendous effect on returns to R&D, which translates directly to market value. The first step in maximizing returns to innovation is knowing RQ.

Armed with knowledge of their RQ, firms can increase their market value almost immediately merely by choosing the right level of R&D investment. As a recent *Harvard Business Review* article by one of the authors, Anne Marie Knott, shows, this benefit alone can be tremendous.[38]

[38] Anne Marie Knott, "The Trillion-Dollar R&D Fix," *Harvard Business Review* (May 2012).

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Arbitrage Risk and Market Efficiency – Applications to Securities Class Actions[1]

Abstract

Measuring the efficiency of the market for a stock is important for a number of reasons. For example, it determines the necessity for an investor to acquire expensive additional information about a firm, and it is a critical factor in class certification in a securities class action. We provide a general methodology to measure the market efficiency percentile for a stock for any relevant period. We apply this methodology to calculate arbitrage risk for each U.S. exchange-listed common stock for every calendar year from 1988 to 2010. We find that market efficiency is significantly affected by turnover (negatively), the number of market makers for Nasdaq stocks (negatively), and serial correlation in the market model of the stock (positively). These findings seem inconsistent with "conventional wisdom," but we show that our findings are consistent with economic logic. The relations between market efficiency and market capitalization (positive), bid-ask spread (negative), institutional ownership (positive), and explanatory power of the relevant market model (positive) are consistent with conventional wisdom. The impact on market efficiency of the number of securities analysts following a stock and the public float ratio of a stock are of ambiguous significance.

I. Introduction

Knowing the level of efficiency of the market for a security is important for a number of reasons.[2] For example, it informs the necessity for an investor to acquire additional information about the firm issuing the security.

[1] The authors sincerely appreciate the detailed comments provided by Reena Aggarwal, Glenn Davis, John Davis, S.P. Kothari, Robert MacLaverty, Leslie Marx, Michael McDonald, David Nelson, Rebecca Nelson, Edward O'Brien, Jeffrey Pontiff, Terence Rodgers, Stephen Rovak, Erik Sirri, Dennis Staats, Robert Thompson, Sanjay Unni, Paul Wazzan, and Simon Wheatley. In addition, Bhattacharya acknowledges discussions with his former colleagues on the faculty at Olin Business School, Washington University in St. Louis, and the resources and financial support provided by the school. He also acknowledges the substantial comments from his distinguished colleagues at, and the resources and intellectual environment provided by, Berkeley Research Group, LLC. The authors, of course, take full responsibility for all opinions and errors. The organizations with which the authors and reviewers are affiliated do not necessarily endorse or share the opinions or conclusions of this paper.

[2] For academic research on market efficiency and its tests, see, e.g., Bradford Cornell, "Spot rates, forward rates and exchange market efficiency," *Journal of Financial Economics (*1977); Michael Brennan and Eduardo Schwartz, "An Equilibrium Model of Bond Pricing and a Test of Market Efficiency," *Journal of Financial and Quantitative Analysis (*1982); Gerald Dwyer and Myles Wallace, "Cointegration and market efficiency," *Journal of International Money and Finance (*2002); Ronald Gilson and Reinier Kraakman, "The Mechanisms of Market Efficiency," *Virginia Law Review (*1984); Michael Jensen, "Some Anomalous Evidence Regarding Market Efficiency,"

Market efficiency is most significantly discussed at the class certification stage of securities fraud cases—the point at which the court determines if the plaintiffs' claims are best tried individually or whether numerous plaintiffs can collectively pursue essentially the same claim against the defendant at the same time. Until the decision in *Basic v. Levinson* (485 U.S. 224 (1988)) and the adoption of the fraud-on-the-market theory, it was difficult for plaintiffs to establish that the reliance element of their claim was common to all class members. It was deemed critical for class certification that the market for the relevant security be efficient. The fraud-on-the-market theory was designed to address this reliance problem. In *Cammer v. Bloom* (D. N.J. 1989), the court enumerated several factors in the determination of market efficiency: (1) the average weekly trading volume, (2) the number of security analysts following and reporting on the security, (3) the extent to which market makers traded the security, (4) the issuer's eligibility to file an SEC registration Form S-3, and (5) the cause-and-effect relationship between material disclosures and changes in the security's price. These *Cammer* factors have been adopted by a number of other courts, and still other courts have added additional considerations. For instance, one court considered the company's market capitalization and the size of the public float for the security, while another considered the ability to sell short the security and the level of autocorrelation between the security's prices.

The market for a security is said to be "semistrong form efficient" if the price of the security reflects all publicly available information. Prices of securities reflect, albeit *to varying extents*, all publicly available information; therefore, markets for securities are semistrong form efficient *in varying degrees*. Much research has also been done to determine the mechanisms by which the pricing signal operates, and it is widely understood that correction of mispricing of a stock occurs primarily through arbitrage activity.[3]

Since arbitrage is not a cost-free activity, and because frictions remain, whether in the form of transaction costs, idiosyncratic risk, or other costs and risks associated with trading securities, pricing anoma-

*Journal of Financial Economics (*1978); S.P. Kothari, "Capital markets research in accounting," *Journal of Economics and Accounting (*2001); Tim Loughran and Jay Ritter, "Uniformly Least Powerful Tests of Market Efficiency," *Journal of Financial Economics (*2000); Burton Malkiel, "Efficient Market Hypothesis," in P. Newman, M. Milgate, and J. Eatwell (eds.), *New Palgrave Dictionary of Money and Finance,* Macmillan, London (1992); Burton Malkiel, "The Efficient Market Hypothesis and Its Critics," *CEPS Working Paper No. 91 (*2003); Rafael Porta, Josef Lakonishok, Andrei Shleifer, and Robert Vishny, "Good News for Value Stocks: Further Evidence on Market Efficiency," *NBER Working Paper No. 5311 (*1995); Richard Roll, "A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market," *The Journal of Finance (*1984); Paul Samuelson, "An Enjoyable Life Puzzling Over Modern Finance Theory," *Annual Review of Financial Economics (*2009); Robert Shiller, "The Use of Volatility Measures in Assessing Market Efficiency," *NBER Working Paper No. 565 (*1981); and Ying Duan, Gang Hu, and R. David McLean, "Costly arbitrage and idiosyncratic risk: Evidence from short sellers," *J. Finan. Intermediation* (2010).

[3] See, e.g., Larry Harris, *Trading & Exchanges: Market Microstructure for Practitioners*, Oxford University Press, Chapters 10 and 17 (2003); and Jeffrey Pontiff, "Costly arbitrage and the myth of idiosyncratic risk," *Journal of Accounting & Economics* (2006).

lies may persist.[4] As a result, everything else remaining the same, financial economics tells us that the market for a stock with a higher arbitrage cost will be less efficient—i.e., a stock's market efficiency is negatively related to its arbitrage risk.[5] Thus, we refer to arbitrage risk as a negative proxy for market efficiency.

Consider an arbitrageur whose information suggests that a stock is underpriced. The arbitrageur will then "go long" on that stock (buy and hold the stock) in order to obtain arbitrage profits by selling the stock at a later date. However, the arbitrageur will also manage the risk of holding the stock by hedging. As a result of our interviews with traders "in the trenches," we model the arbitrageur as choosing the optimal hedge stocks and the optimal hedge ratios. The risk of this optimal arbitrage portfolio is the arbitrage risk of the stock, our negative proxy for market efficiency. We discuss these calculations in detail.

We provide a methodology that can calculate the market efficiency percentile of a stock over the relevant period, based on the data for a comparable measurement period.[6] For example, in *Lefkoe, et al. v. Jos. A. Bank Clothiers, Inc.*, where the class period was January 5, 2006, to June 7, 2006, we used August 1, 2005, to January 4, 2006, as the measurement period. We concluded that the market for Jos. A. Bank Clothiers common stock was at the 40th percentile for efficiency over the class period.

If it is not possible (or desirable) to use a different measurement period—e.g., if the period of interest immediately follows an initial public offering (IPO)—then we can do the calculations with the measurement period as the relevant period, and we call this the *ex post* arbitrage risk of the security for the relevant period. For example, in a recent securities class action filed against Groupon, Inc., the class period was defined as November 4, 2011, to March 30, 2012. Since the class period immediately follows the IPO, we do not have trading data from a prior period to use as the measurement period. Using the class period as the measurement period, we concluded that the market for Groupon common stock was at the 10th percentile for efficiency over the class period.

For this paper, we focus on *ex ante* (baseline) arbitrage risk, but we do sensitivity analyses with *ex post* arbitrage risk as another negative proxy for market efficiency. We apply this methodology to calculate, on a yearly basis, the arbitrage risk for each U.S. exchange-listed common stock from 1988 to 2010

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[4] See, e.g., Jeffrey Pontiff, "Costly arbitrage and the myth of idiosyncratic risk," *Journal of Accounting & Economics* (2006).

[5] This implies that Market Efficiency Percentile – 1 = 100 – Arbitrage Risk Percentile. For example, if a stock is at the 25th percentile for arbitrage risk, then the stock is at the 76th percentile for market efficiency.

[6] We interpret comparability to mean a time interval that is proximate in location and length.

(subject to certain restrictions). We also perform a regression analysis of arbitrage risk (as a negative proxy of market efficiency) on the factors identified by courts in securities class actions. These results are summarized in Table 1.[7]

Table 1: Market Efficiency Results

Factor	Relation with Market Efficiency	Significance at 5% Level	Consistency with "Conventional Wisdom"
Cammer v. Bloom			
Turnover	**Negative**	Significant	**Inconsistent**
Number of Analysts	**Negative**	Ambiguous	—
Number of Nasdaq Market Makers	**Negative**	Significant	**Inconsistent**
Unger v. Amidesys			
Market Capitalization	**Positive**	Significant	**Consistent**
Bid-Ask Spread	**Negative**	Significant	**Consistent**
Public Float Ratio	**Positive**	Ambiguous	—
Other			
Institutional Ownership Ratio	**Positive**	Significant	**Consistent**
Serial Correlation	**Positive**	Significant	**Inconsistent**
Explanatory Power	**Positive**	Significant	—
Inclusion in Dow Jones Index	**Negative**	Significant	—

We checked the sensitivity of these results through a number of additional analyses. For one set, we replaced turnover with logarithm of volume (or logarithm of dollar volume) but removed market capitalization from the list of factors, reflecting the fact that, ceteris paribus, the volume for a stock with higher market capitalization will be higher. For this set, we found that the results were the same as in Table 1, except that market efficiency was positively and significantly affected by number of analysts; positively but insignificantly affected by number of market makers (for Nasdaq stocks); positively but ambiguously affected by serial correlation; and positively and significantly affected by inclusion in the DJIA (the latter makes sense because in this set, market capitalization is not used as an explanatory factor, whereas it was used as such for the results in Table 1). The second set uses only the Cammer factors as explanatory variables. For this set, we found that the results were the same as in Table 1, except that market efficiency is positively but insignificantly affected by logarithm of volume (or logarithm of dollar volume); and positively and significantly affected by number of analysts.

[7] We detail all the variables in Section 4. We use 5% as our level of significance. If the significance results are different between under homoscedasticity and under heteroscedasticity-robustness (see Halbert White, "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica,* (1980)), we refer to the significance as ambiguous.

In Section 2, we detail the development and application of market efficiency to securities class actions. In Section 3, we develop arbitrage risk as a negative proxy for market efficiency. In Section 4, we provide regression results that test the various factors believed to determine market efficiency—we also investigate the empirical findings that are apparently inconsistent with "conventional wisdom" and show that the empirical findings are actually consistent with the principles of financial economics. Section 5 concludes the paper.

II. Market Efficiency and Securities Class Actions

General acceptance of the relevance of the efficient market hypothesis by the courts arose with the case of *Basic, Inc. v. Levinson,* 485 U.S. 224 (1988), in which the U.S. Supreme Court adopted the fraud-on-the-market theory. Although courts recognize that the efficient market hypothesis is not without its critics,[8] in a decision handed down on June 6, 2011, the Supreme Court once again restated the principles of the *Basic* decision.[9]

Assessment of market efficiency is most significant at the class certification stage of securities fraud cases, the point at which the court resolves whether the plaintiffs' claims are best tried individually or whether numerous plaintiffs can collectively pursue essentially the same claim against the defendant at the same time. In order to establish a typical claim of securities fraud, usually pursued under Section 10(b) of the Securities Exchange Act of 1934, plaintiffs must prove (1) a material misrepresentation or omission by a defendant, (2) scienter, (3) a connection between the misrepresentation or omission and the purchase or sale of a security, (4) reliance upon the misrepresentation or omission, (5) economic loss, and (6) loss causation.[10]

At the class certification stage of a case, plaintiffs need not prove each of these elements on the merits, but they must show that questions of law or fact common to all class members predominate over any questions affecting only individual members, and that a class action is superior to other available methods for fairly and efficiently adjudicating the controversy.[11] Until the adoption of the fraud-on-the-market theory in *Basic*, it was difficult for plaintiffs to establish that the reliance element of their claim was common to all class members, and that all class members relied on the same information

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[8] See *In re Polymedica Corp. Sec. Litig.*, 432 F.3d 1, 10, n. 15 (1st Cir. 2005).

[9] *Erica P. John Fund, Inc. v. Halliburton Co.*, No. 09-1403, 2011 WL 2175208, at *1 (June 6, 2011).

[10] *Stoneridge Inv. Partners, LLC v. Scientific-Atlanta, Inc.*, 552 U.S. 148, 157 (2008).

[11] Fed. R. Civ. P. 23(b)(3).

and to the same degree in making their securities purchases or sales. Indeed, many, if not most, class members had difficulty establishing reliance at all since they likely bought or sold the underlying security without direct knowledge of the alleged misrepresentation or omission. The fraud-on-the-market theory was designed to address this reliance problem.

The fraud-on-the-market theory avoids the reliance pitfall by providing plaintiffs with a rebuttable presumption of reliance upon the alleged misrepresentations so long as the market for the underlying security is efficient.[12] The notion is that, in an open and developed securities market, the price of a security is determined by the publicly available information about the underlying company, including the alleged misrepresentation.[13] At the class certification stage, plaintiffs can present evidence that they traded shares in an efficient market. The court then presumes (1) that the market price of the security incorporates all information, including the alleged misrepresentation; (2) that the plaintiffs actually relied on the market price of the security as an indicator of its value; and (3) that the plaintiffs acted reasonably in doing so. Defendants can rebut the presumption of reliance by presenting any defense challenging actual reliance or market efficiency.[14] Based on the evidence presented, the court then decides whether or not the matter can legitimately proceed as a class action.

Thus, federal district courts have been instructed to conduct rigorous analyses of market efficiency at the class certification stage of securities lawsuits.[15] However, the legal system has not developed a systematic standard for determining whether a particular market is efficient for purposes of applying the fraud-on-the-market presumption of investor reliance. The analysis is typically addressed by financial experts who present evidence to the court, with the court then making a legal determination about whether the pertinent market was "efficient enough."

Although presentation of evidence is left to the parties and the particulars of each case, courts have supplied guidance on factors that should be considered in making determinations about market efficiency. In addition to the *Cammer* factors referred to earlier,[16, 17] such factors include market capitaliza-

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[12] *DVI, Inc. Sec. Litig.*, 639 F.3d at 631 (2010).

[13] *Erica P. John Fund, Inc.*, No. 09-1403, 2011 WL 2175208, at *1 (June 6, 2011).

[14] *Basic,* 485 U.S. at 248.

[15] *DVI, Inc. Sec. Litig.*, 639 F.3d at 633 (2010); *In re Hydrogen Peroxide Antitrust Litig.*, 552 F. 3d 305, 309–10 (3rd Cir. 2009).

[16] *Cammer v. Bloom*, 711 F. Supp. 1264, 1286–87 (D. N.J. 1989).

[17] See *DVI, Inc. Sec. Litig.*, 639 F.3d at 633 n.14 (2010); *Teamsters Local 445 Freight Div. Pension Fund v. Bombardier, Inc.*, 546 F.3d 196, 204 n. 11 (2d Cir. 2008); *In re Xcelera.com Sec. Litig.*, 430 F.3d 503, 508 (1st Cir. 2005); *Unger v. Amedisys Inc.*, 401 F.3d 316, 323 (5th Cir. 2005); *Gariety v. Grant Thornton, LLP*, 368 F.3d 356, 368 (4th Cir. 2004); *Binder v. Gillespie,* 184 F. 3d 1059, 1064–65 (9th Cir. 1999).

tion, size of the public float,[18] ability to sell short the security, and level of autocorrelation between the security's prices.[19]

III. Arbitrage Risk as a Negative Proxy for Market Efficiency

Capital market efficiency describes how completely and accurately the pricing signal works. When all publicly available information is reflected in a security's price, the market for the security is said to be semistrong form efficient.[20] We interpret the concept not as an either/or, binary construct, but rather as a relative concept occurring along a continuum, and thus one often refers to a market's *relative efficiency.*[21] The pricing signal is thought to work through the actions of all traders who, whatever their level of knowledge and sophistication, convey their individual valuations to the market through their buy and sell decisions at various price points.[22] The collective actions of all traders thus push the price of a particular security toward its market equilibrium level, but do not necessarily take the market for the security all the way to perfect semistrong form efficiency.

Arbitrageurs are investors who trade on information about relative values. They trade investments that are or should be fundamentally correlated but for which they believe the market valuations are deviating from the fundamental relation. Thus arbitrageurs attempt to take advantage of the market pricing discrepancies between otherwise fundamentally correlated securities in order to earn trading profits. This activity of exploiting situations in which markets are not efficient assists the pricing signal by conveying information to the market and helping to push the market to efficiency, but does not necessarily take the market all the way to perfect semistrong form efficiency.

But as Pontiff explains, because of "costly arbitrage," arbitrageurs are unlikely to ever completely eliminate mispricing.[23] He identifies two sources of arbitrage costs: transactions costs (e.g., commissions, brokerage fees) and holding costs (e.g., opportunity cost of capital and the idiosyncratic risk of

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[18] See *Krogman v. Sterritt*, 202 F.R.D. 467, 478 (N.D. Tex. 2001).

[19] See *In re Polymedica Corp. Sec. Litig.*, 432 F.3d 1, 18 at n. 21 (1st Cir. 2005).

[20] See Eugene Fama, "Efficient Capital Markets: A Review of Theory and Empirical Work," *Journal of Finance* (1970); and Burton Malkiel, "Efficient Market Hypothesis," in P. Newman, M. Milgate, and J. Eatwell (eds.), *New Palgrave Dictionary of Money and Finance*, Macmillan, London (1992).

[21] See, e.g., John Campbell, Andrew Lo, and A. Craig MacKinlay, *The Econometrics of Financial Markets,* Princeton University Press, Princeton, NJ (1997).

[22] See, e.g., Larry Harris, *Trading & Exchanges: Market Microstructure for Practitioners*, Oxford University Press, Chapters 10 and 17 (2003).

[23] Jeffrey Pontiff, "Costly arbitrage and the myth of idiosyncratic risk," *Journal of Accounting & Economics* (2006).

a security), and he stresses the importance of idiosyncratic risk in making arbitrage a costly endeavor.[24] As arbitrageurs construct their hedge portfolios of investments, supposedly correlated in returns, they cannot find perfectly positive correlations in returns and thus perfect substitutes as investments (or perfectly negative correlations in returns and perfect complements as investments), so they are always exposed to the vagaries of each individual security they hold. Even aggregated across a number of investment positions within the hedge portfolio, the legs of the arbitrage, arbitrageurs cannot eliminate the idiosyncratic risk of any security.

As a result of the costs of arbitrage, including idiosyncratic risk, market inefficiencies will always remain; the better arbitrage works, the more efficient the market for a security is likely to be. As a result, the costs of arbitrage for a security provide a means to test the efficiency of the security.

Pontiff concludes that "idiosyncratic risk is the single largest cost faced by arbitrageurs," and that "idiosyncratic risk is the single largest barrier to arbitrage."[25] Our notion of arbitrage risk is a generalization of the standard notion of idiosyncratic risk, defined as the standard deviation of residuals from a standard one-factor market model, also known as the Capital Asset Pricing Model (CAPM).[26] If an arbitrageur is constrained to having access to only the market index and a risk-free instrument to devise an optimal zero-net-investment arbitrage portfolio, then the risk of the resulting optimal arbitrage portfolio is the standard idiosyncratic risk. For our notion of *ex ante* or *ex post* arbitrage risk, however, we model the arbitrageur as optimally choosing the components of the arbitrage portfolio from the universe of the market index *and* all exchange-listed U.S. common stocks, based on financial data on the returns of the stock of interest, all candidate securities, and the risk-free instrument over the measurement period.[27] Then, given the optimal choice of the components of the arbitrage portfolio, and the risk-free instrument, we model the arbitrageur as choosing the optimal hedge ratios under a zero-net-investment constraint. The risk of this optimal arbitrage portfolio is the arbitrage risk of the stock, our negative proxy for market efficiency. Our interviews with traders "in the trenches" confirm this overall structure of hedging behavior by arbitrageurs.

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[24] *Id.*

[25] *Id.*

[26] See, e.g., William Sharpe, "Capital asset prices: A theory of market equilibrium under conditions of risk," *Journal of Finance* (1964); Harry Markowitz, "The early history of portfolio theory: 1600–1960," *Financial Analysts Journal* (1999); and Merton Miller, "The History of Finance," *The Journal of Portfolio Management* (1999).

[27] The optimal choice of hedge securities is detailed in Rajeev Bhattacharya, "Structural Models of Market Efficiency," *Mimeo (2012).* Jeffrey Wurgler and Ekaterina Zhuravskaya, "Does Arbitrage Flatten Demand Curves for Stocks," *Journal of Business* (2002), use a different set of criteria for the selection of optimal hedge securities.

We thus develop a practical and general (negative) proxy for market efficiency by quantifying the arbitrage risk associated with each individual security. This simple (negative) proxy for market efficiency then allows for an examination of a variety of factors that have been proffered by economists and lawyers as affecting market efficiency.

We calculate the arbitrage risk of a stock over a defined relevant period as follows:

- We select the relevant period, which can be a day, a week, a court-determined "class" period, or other time frame of relevance (simply for presentation in this paper, we have chosen annual periods).

- We choose a period immediately prior to the relevant period as the measurement period, because the arbitrageur would not have had access to relevant-period data at the beginning of the relevant period (also for simplicity, we have chosen the year prior to the relevant period as the measurement period).

- On the basis of the measurement period, we determine the lowest risk portfolio that an arbitrageur would use to benefit from mispricing, as explained above. We call this portfolio the arbitrage portfolio for the stock.

- The *ex ante* (or baseline) arbitrage risk of the security for the relevant period is the risk of the arbitrage portfolio over the relevant period.

If it is not possible (or desirable) to use a different measurement period—e.g., if the period of interest immediately follows an initial public offering—then we can do the calculations where the measurement period is the same as the relevant period, and we call this the *ex post* arbitrage risk of the security for the relevant period. For this paper, we focus on *ex ante* (baseline) arbitrage risk, but we perform sensitivity analyses with *ex post* arbitrage risk as another negative proxy for market efficiency.

Consider a stock that is underpriced (overpriced) according to the information available to an arbitrageur. In order to exploit this profitable opportunity, the arbitrageur will construct the following arbitrage portfolio with zero net investment, thereby reaping arbitrage profits when closing out the investment portfolio:

- Arbitrage numerator: go long (short) on the mispriced stock; let's say by $1 (purely a normalization).

- Other arbitrage legs:
    - Go short (long) on *N* other securities. We use *N = 5* legs for the baseline model, but the results do not change substantively with values of *N = 10* or *20.*
    - Go short (long) on the risk-free asset.
    - The total amount on these legs has to add up to $1 short (long).
    - How much to go short (long) on each leg is called the corresponding Hedge Ratio.[28]

The risk of a portfolio over a period is defined as the standard deviation of daily returns of the portfolio over that period. Since the arbitrageur does not have access to all relevant period data at the beginning of the relevant period, we choose a period immediately prior to the relevant period as the measurement period, and the arbitrage portfolio is selected to minimize the risk (i.e., the standard deviation of daily returns) of the arbitrage portfolio[29] over the measurement period, with the requirement described above that the arbitrage portfolio require zero investment. The risk of the arbitrage portfolio over the relevant period is the arbitrage risk of the stock for the relevant period. For this paper:

- We measure arbitrage risk for U.S. exchange-listed common stocks,
- We consider only U.S. exchange-listed common stocks, and stock indices, as candidate legs of the hedge portfolio,
- We treat the S&P 500 index as just another candidate leg of the hedge portfolio, and
- We use daily returns on six-month U.S. Treasury bills as the daily risk-free rate.[30]

Table 2 shows examples of exchange-listed stocks and their estimated market efficiency percentiles in 2010, on the basis of our measure of arbitrage risks of all U.S. exchange-listed common stocks.

[28] We use a computational simplification provided by Jeffrey Wurgler and Ekaterina Zhuravskaya, "Does Arbitrage Flatten Demand Curves for Stocks," *Journal of Business (*2002).

[29] Arbitrageurs generally construct hedge portfolios to minimize the total risk of the portfolio. See Larry Harris, *Trading & Exchanges: Market Microstructure for Practitioners,* Oxford University Press, p. 348 (2003).

[30] Treasury Constant Maturities, from Federal Reserve, H15 Report.

Table 2: Examples of Market Efficiency Percentiles in 2010

Ticker	Company	Market Efficiency Percentile
ADP	AUTOMATIC DATA PROCESSING INC	100
BRK	BERKSHIRE HATHAWAY INC DEL	100
DUK	DUKE ENERGY CORP NEW	100
ED	CONSOLIDATED EDISON INC	100
HNZ	HEINZ H J CO	100
JNJ	JOHNSON & JOHNSON	100
JW	WILEY JOHN & SONS INC	100
MO	ALTRIA GROUP INC	100
NST	NSTAR	100
ADM	ARCHER DANIELS MIDLAND CO	91
CAT	CATERPILLAR INC	91
CSCO	CISCO SYSTEMS INC	91
EMC	E M C CORP MA	91
BLK	BLACKROCK INC	81
CBT	CABOT CORP	81
ENDP	ENDO PHARMACEUTICALS HLDNGS INC	81
GPS	GAP INC	81
AMZN	AMAZON COM INC	80
AXP	AMERICAN EXPRESS CO	80
ACF	AMERICREDIT CORP	51
CIEN	CIENA CORP	51
COBZ	COBIZ FINANCIAL INC	51
CPHD	CEPHEID	51
DAL	DELTA AIR LINES INC	51
ACAT	ARCTIC CAT INC	26
APKT	ACME PACKET INC	26
ARTW	ARTS WAY MANUFACTURING INC	26
ATAC	A T C TECHNOLOGY CORP	26
AVII	A V I BIOPHARMA INC	26
TEAR	OCCULOGIX INC	1
TLX	TRANS LUX CORP	1
TSTR	TERRESTAR CORP	1
VNDA	VANDA PHARMACEUTICALS INC	1
ZANE	ZANETT INC	1

Table 3 demonstrates that different stocks display different patterns of market efficiency across time.

Table 3: Examples of Market Efficiency Percentiles Over Time

Ticker	Company Name	Year	Market Efficiency Percentile
ALG	ALAMO GROUP INC	2001	96
ALG	ALAMO GROUP INC	2002	83
ALG	ALAMO GROUP INC	2003	95
ALG	ALAMO GROUP INC	2004	68
ALG	ALAMO GROUP INC	2005	46
ALG	ALAMO GROUP INC	2006	54
ALG	ALAMO GROUP INC	2007	60
ALG	ALAMO GROUP INC	2008	68
ALG	ALAMO GROUP INC	2009	47
ALG	ALAMO GROUP INC	2010	58
CNLG	CONOLOG CORP	2001	2
CNLG	CONOLOG CORP	2002	3
CNLG	CONOLOG CORP	2003	3
CNLG	CONOLOG CORP	2004	1
CNLG	CONOLOG CORP	2005	2
CNLG	CONOLOG CORP	2006	1
CNLG	CONOLOG CORP	2007	1
CNLG	CONOLOG CORP	2008	1
CNLG	CONOLOG CORP	2009	3
CNLG	CONOLOG CORP	2010	2
ED	CONSOLIDATED EDISON INC	2001	100
ED	CONSOLIDATED EDISON INC	2002	98
ED	CONSOLIDATED EDISON INC	2003	100
ED	CONSOLIDATED EDISON INC	2004	100
ED	CONSOLIDATED EDISON INC	2005	100
ED	CONSOLIDATED EDISON INC	2006	100
ED	CONSOLIDATED EDISON INC	2007	100
ED	CONSOLIDATED EDISON INC	2008	100
ED	CONSOLIDATED EDISON INC	2009	100
ED	CONSOLIDATED EDISON INC	2010	100

Table 3: Examples of Market Efficiency Percentiles Over Time (continued)

Ticker	Company Name	Year	Market Efficiency Percentile
FRE	FEDERAL HOME LOAN MORTGAGE CORP	2001	100
FRE	FEDERAL HOME LOAN MORTGAGE CORP	2002	100
FRE	FEDERAL HOME LOAN MORTGAGE CORP	2003	91
FRE	FEDERAL HOME LOAN MORTGAGE CORP	2004	97
FRE	FEDERAL HOME LOAN MORTGAGE CORP	2005	94
FRE	FEDERAL HOME LOAN MORTGAGE CORP	2006	95
FRE	FEDERAL HOME LOAN MORTGAGE CORP	2007	40
FRE	FEDERAL HOME LOAN MORTGAGE CORP	2008	3
FRE	FEDERAL HOME LOAN MORTGAGE CORP	2009	3
MSFT	MICROSOFT CORP	2001	55
MSFT	MICROSOFT CORP	2002	89
MSFT	MICROSOFT CORP	2003	92
MSFT	MICROSOFT CORP	2004	96
MSFT	MICROSOFT CORP	2005	98
MSFT	MICROSOFT CORP	2006	87
MSFT	MICROSOFT CORP	2007	95
MSFT	MICROSOFT CORP	2008	95
MSFT	MICROSOFT CORP	2009	89
MSFT	MICROSOFT CORP	2010	95

IV. Relation of Arbitrage Risk to Standard Factors: Empirical Findings

We test the empirical relation with arbitrage risk (as a negative proxy for market efficiency) of factors relied upon by courts and others as determinants of market efficiency.[31] This is done for all U.S. exchange-listed common stocks from 1988 (the year of the landmark *Basic* decision detailed in Section 2) to 2010, the last year for which we have full data, with the following restrictions.

We restricted attention to stock-year combinations consisting of stocks that had one PERMNO, one ticker, and one CUSIP over the year in the Center for Research in Security Prices (CRSP) Daily Stock

[31] Brad Barber, Paul Griffin, and Baruch Lev, "The Fraud-on-the-Market Theory and the Indicators of Common Stocks' Efficiency," *The Journal of Corporation Law (*1994), use a different proxy.

Database. We utilized each stock available from CRSP,[32] for which the following data exist for at least 75% of trading days during each of the relevant and measurement periods:

- Returns
- Shares outstanding
- Trading volume
- Closing bid
- Closing ask
- Exchange membership
- Number of market makers.

To include a particular stock in our analysis, we also required data to be available for:

- The number of securities analysts (from I/B/E/S)
- Insider holdings (from Thomson Reuters)
- Institutional holdings (from Thomson Reuters)
- Inclusion in the Dow Jones Industrial Average (DJIA) index (from Phyllis Pierce, The Dow Jones Averages 1885–1995).

Appendix 1 shows the number of stocks at the various stages after imposing the restrictions described above.

From this data, we develop measures for the various factors that courts and others have relied upon as influencing market efficiency. These measures are each defined below.

- Turnover: mean daily turnover (volume)/(shares outstanding) over the relevant period.

[32] *shrcd* = 10 or 11 in the Daily Stock Database from the Center for Research in Security Prices.

- Number of security analysts: number of security analysts who announced at least one projection about the security during the relevant period.

- Number of market makers for Nasdaq stocks: highest, over the relevant period, of the number of market makers on each day.

- Market capitalization: mean of daily logarithm of market capitalization over the relevant year.

- Bid-ask spread: mean of daily relative spread (closing ask − closing bid)/(closing price) over the relevant period.

- Public float ratio: mean of quarterly public float ratio (shares outstanding − insider holdings)/(shares outstanding) over the relevant period.

- Institutional ownership ratio: institutional ownership ratio (institutional holdings)/(shares outstanding) over the relevant period.

- Serial correlation in market model: By performing the Durbin-Watson Test on the standard one-factor market model on daily returns for a stock for a calendar year, we obtain the p-value for positive serial correlation and the p-value for negative serial correlation.[33] The negative of the minimum of these p-values is a positive measure of serial correlation in the one-factor market model for the particular stock for the relevant year.

- Explanatory power of market model: R2 of the standard one-factor market model for the security in the relevant period.

- Inclusion in the DJIA: If a stock is on the DJIA for an entire year, the indicator variable for that stock for that year is one. If a stock is not on the DJIA for an entire year, the indicator variable for that stock for that year is zero. If a stock is on the DJIA for only part of the year, the observation for that stock for that year is deleted from the regression.

Summary statistics for arbitrage risk and for each of the explanatory variables are shown in Appendix 2.

[33] See, e.g., William Greene, *Econometric Analysis,* Prentice Hall (2000).

For this paper, we perform a reduced-form regression[34] of arbitrage risk[35] on various factors of market efficiency, controlling for year. The results of this regression—which uses 35,587 observations (stock-years) and has $R^2 = 0.463$ and adjusted $R^2 = 0.462$ (see Appendix 3)—are shown in Table 4.[36]

Table 4: Detailed Regression Results

Dependent Variable: Arbitrage Risk							
		Under Homoscedasticity			**Heteroscedasticity-Robust**		
Factor	**Coefficient**	**Standard Error**	**t-Statistic**	**p-Value**	**Standard Error**	**t-Statistic**	**p-Value**
Cammer v. Bloom							
Turnover	74.366%	3.881%	19.160	<0.0001	6.286%	11.830	<0.0001
Number of Analysts	0.006%	0.004%	1.770	0.077	0.002%	3.100	0.0019
Number of Nasdaq Market Makers	0.019%	0.003%	5.780	<0.0001	0.004%	4.880	<0.0001
Unger v. Amidesys							
Market Capitalization	-0.406%	0.032%	-12.880	<0.0001	0.043%	-9.360	<0.0001
Bid-Ask Spread	48.975%	1.750%	27.980	<0.0001	9.077%	5.400	<0.0001
Public Float Ratio	-0.821%	0.179%	-4.600	<0.0001	0.880%	-0.930	0.3508
Other							
Institutional Ownership Ratio	-0.629%	0.138%	-4.560	<0.0001	0.142%	-4.420	<0.0001
Serial Correlation	-0.423%	0.195%	-2.170	0.03	0.148%	-2.860	0.0042
Explanatory Power	-1.411%	0.280%	-5.040	<0.0001	0.166%	-8.520	<0.0001
Inclusion in Dow Jones Index	1.030%	0.295%	3.490	0.0005	0.136%	7.550	<0.0001
Listed on NYSE	0.467%	0.145%	3.220	0.0013	0.153%	3.040	0.0024
Listed on AMEX	-0.351%	0.163%	-2.150	0.0314	0.112%	-3.150	0.0016
Listed on Other Exchange	0.800%	2.255%	0.350	0.7227	0.640%	1.250	0.2113
Year 1988	6.788%	0.571%	11.890	<0.0001	0.878%	7.730	<0.0001
Year 1989	7.640%	0.550%	13.900	<0.0001	0.872%	8.760	<0.0001
Year 1990	12.130%	0.563%	21.550	<0.0001	1.267%	9.570	<0.0001
Year 1991	45.566%	0.568%	80.230	<0.0001	4.618%	9.870	<0.0001
Year 1992	11.421%	0.464%	24.610	<0.0001	0.976%	11.700	<0.0001
Year 1993	6.968%	0.457%	15.240	<0.0001	0.850%	8.190	<0.0001

[34] In Rajeev Bhattacharya, "Structural Models of Market Efficiency," *Mimeo* (2012), we use Errors-In-Variables (EIV) methods to incorporate the proxies, and we use the panel nature of the data to identify appropriate instruments for the proxy variables, and for the endogenous variables. We apply Three-Stage Least Squares (3SLS) to implement a Seemingly Unrelated (SUR) equations estimation of these structural models, separately for all Nasdaq and all non-Nasdaq U.S. common stocks, for the period from 2001 to 2010.

[35] It is worth noting again that, *ceteris paribus,* market efficiency has a negative relation with arbitrage risk.

[36] See Halbert White, "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica* (1980), for a description of testing methods that are robust to the presence of heteroscedasticity.

Table 4: Detailed Regression Results (continued)

Dependent Variable: Arbitrage Risk		Under Homoscedasticity			Heteroscedasticity-Robust		
Factor	**Coefficient**	**Standard Error**	**t-Statistic**	**p-Value**	**Standard Error**	**t-Statistic**	**p-Value**
Other (continued)							
Year 1994	6.826%	0.449%	15.210	<0.0001	0.852%	8.010	<0.0001
Year 1995	6.743%	0.447%	15.070	<0.0001	0.853%	7.910	<0.0001
Year 1996	7.066%	0.444%	15.920	<0.0001	0.856%	8.260	<0.0001
Year 1997	7.381%	0.439%	16.830	<0.0001	0.852%	8.670	<0.0001
Year 1998	7.968%	0.433%	18.420	<0.0001	0.848%	9.400	<0.0001
Year 1999	7.966%	0.437%	18.210	<0.0001	0.856%	9.300	<0.0001
Year 2000	8.747%	0.436%	20.070	<0.0001	0.859%	10.180	<0.0001
Year 2001	8.742%	0.424%	20.610	<0.0001	0.840%	10.400	<0.0001
Year 2002	8.539%	0.414%	20.620	<0.0001	0.830%	10.290	<0.0001
Year 2003	7.963%	0.412%	19.330	<0.0001	0.819%	9.730	<0.0001
Year 2004	7.801%	0.417%	18.730	<0.0001	0.823%	9.480	<0.0001
Year 2005	7.694%	0.416%	18.480	<0.0001	0.823%	9.340	<0.0001
Year 2006	7.684%	0.415%	18.510	<0.0001	0.824%	9.320	<0.0001
Year 2007	8.080%	0.411%	19.650	<0.0001	0.825%	9.800	<0.0001
Year 2008	9.465%	0.399%	23.710	<0.0001	0.828%	11.430	<0.0001
Year 2009	9.677%	0.393%	24.630	<0.0001	0.823%	11.760	<0.0001
Year 2010	7.928%	0.396%	20.010	<0.0001	0.820%	9.670	<0.0001

As with the results summarized in Table 1, we checked the sensitivity of these results through a number of additional analyses. For one set, we replaced turnover with logarithm of volume (or logarithm of dollar volume) but removed market capitalization from the list of factors, reflecting the fact that, ceteris paribus, the volume for a stock with higher market capitalization will be higher. For this set, we found that the results were the same as in Table 4, except that arbitrage risk was negatively and significantly affected by number of analysts; negatively but insignificantly affected by number of market makers (for Nasdaq stocks); negatively but ambiguously affected by serial correlation; and negatively and significantly affected by inclusion in the DJIA (the latter makes sense because in this set, market capitalization is not used as an explanatory factor, whereas it was used as such for the results in Table 4). The second set uses only the Cammer factors as explanatory variables. For this set, we found that the results were the same as in Table 4, except that arbitrage risk is negatively but insignificantly affected by logarithm of volume (or logarithm of dollar volume); and negatively and significantly affected by number of analysts.

Trading Volume

The positive relation of trading volume or turnover with market efficiency is often considered almost axiomatic—statements such as "the more thinly traded the stock, the less efficient the market is" are common. However, this is not necessarily the case.[37] In order to appreciate how trading volume (or turnover) is often misunderstood, we need to appreciate that:

> *[I]nvestors trade among themselves because they are different. . . . The difference in their response to the same information generates trading. The greater the information asymmetry, the larger the abnormal trading volume when public news arrives.*[38]

We would observe higher trading volume or turnover in the market for an asset if and only if:[39]

(1) Transaction costs (including bid-ask spread, commissions, and search costs) are low relative to dispersion in investor valuations.

(2) Low-valuers hold more securities than high-valuers, and short sales costs are low relative to dispersion in investor valuations.

Higher trading volume will therefore be observed with:

- Lower transaction costs,
- Lower short sales costs,
- Higher dispersion of investor valuations, and/or

37 See also Jonathan Karpoff, "The Relation Between Price Changes and Trading Volume: A Survey," *Journal of Financial and Quantitative Analysis (*1987); Maureen O'Hara, *Market Microstructure Theory,* Blackwell Publishing, Malden, MA (1997); Scott Stickel and Robert Verrecchia, "Evidence that Trading Volume Sustains Stock Price Changes," *Financial Analysts Journal (*1994); Lawrence Blume, David Easley, and Maureen O'Hara, "Market Statistics and Technical Analysis: The Role of Volume, *Journal of Finance (*1994); and Erik Sirri, Edie Hotchkiss, and Michael Goldstein, "Transparency and Liquidity: A Controlled Experiment on Corporate Bonds," *Review of Financial Studies* (2007).

38 Jiang Wang, "A Model of Competitive Stock Trading Volume," *Journal of Political Economy (*1994).

39 See Rajeev Bhattacharya, "Structural Models of Market Efficiency," *Mimeo (*2012), for detailed derivations.

- Higher likelihood that an investor holds the asset.

Clearly, market efficiency would be facilitated by lower transaction costs and lower short sales costs—and when a claim is made about higher trading volume being a factor favoring market efficiency, it is often implicitly based on this argument. However, there is no reason to conclude that, *ceteris paribus*, a higher dispersion in investor valuations, or a higher likelihood that an investor holds the asset, would lead to higher market efficiency.[40]

Given these contrary dependencies, the relation of market efficiency with turnover is fundamentally an empirical question, and our empirical finding, for all U.S. exchange-listed common stocks from 1988 to 2010,[41] is that turnover negatively and significantly affects market efficiency. Courts that have used trading volume (or logarithm of volume, dollar volume, or turnover) as a factor favorable to a finding of market efficiency may have done so in error.

The Number of Market Makers

From the above discussion, we can see that the demand for market making services in a Nasdaq stock is an increasing function of dispersion in investor valuations—i.e., everything else remaining the same, a firm is more likely to be a market maker in a Nasdaq stock if the investor valuation profile for that stock is more dispersed, because there would be more trades to enable more profits.

However, the higher the number of market makers, the higher the competition for trades would be, and this would reduce the transaction costs of trades. Therefore, a higher number of market makers would be observed with higher dispersion (not unambiguously facilitating market efficiency, as shown above) and/or lower transaction cost (facilitating market efficiency).

Therefore, as above, the relation between the number of Nasdaq market makers and market efficiency is fundamentally empirical, and our empirical finding, for all U.S. exchange-listed common stocks from 1988 to 2010,[42] is that arbitrage risk for a Nasdaq stock is positively and significantly related to

[40] With high dispersion in investor valuations, we can have a high trading volume (much of which can be due to noise trading), and a higher dispersion in investor valuations does not necessarily add to the efficiency of a market. See Rajeev Bhattacharya, "Structural Models of Market Efficiency," *Mimeo (*2012), for an example where there is no dispersion in valuations and the market is perfectly semistrong form efficient (with no trades).

[41] Restrictions are detailed at the beginning of Section 4.

[42] Restrictions are detailed at the beginning of Section 4.

the number of market makers for that stock; and that market efficiency for a Nasdaq stock is negatively and significantly related to the number of market makers for that stock.

Serial Correlation

Serial correlation in the one-factor market model of a stock's daily returns, suggesting a day-to-day pattern of repeated performance, and is often considered evidence of market inefficiencies. Some scholars have suggested other explanations[43] of serial correlation that are consistent with market efficiency.

In the presence of such inconsistent findings, this dependence becomes an empirical question. Our empirical findings suggest that, on the basis of all U.S. exchange-listed common stocks from 1988 to 2010,[44] serial correlation affects market efficiency positively and significantly, which suggests that relying on serial correlation as a factor against a finding of market efficiency may be inappropriate.

Other Factors

The number of securities analysts is a *Cammer* factor, and other courts have suggested using public float as a factor favorable to a finding of market efficiency. Our empirical findings suggest that, on the basis of all U.S. exchange-listed common stocks from 1988 to 2010,[45] the number of securities analysts and public float have an ambiguous impact on market efficiency, which further suggests that relying on the number of securities analysts or public float for a finding of market efficiency or inefficiency may be inappropriate.

Consistent with the position taken by courts and others, we find that market capitalization, institutional ownership, and the explanatory power of the relevant one-factor market model all have significant empirical support based on our analysis. The bid-ask spread of a stock, which is a measure of transaction cost of a stock, has been used by courts as a factor inhibiting market efficiency, and our results confirm this position, too.

Although we have not found a court ruling where the inclusion of the relevant stock in a major index is a factor favorable to a finding of market efficiency, expert reports and testimony commonly use such

[43] See, e.g., Ray Ball and S.P. Kothari, "Nonstationary expected returns: Implications for Tests of Market Efficiency and Serial Correlation in Returns," *Journal of Financial Economics (*1989).

[44] Restrictions are detailed at the beginning of Section 4.

[45] Restrictions are detailed at the beginning of Section 4.

an argument. It is interesting to note, however, that because we control for market capitalization, what the indicator variable corresponding to membership in the DJIA measures is purely how much the inclusion of the stock in the DJIA adds to the efficiency of the market for the stock, over and above what the stock's market capitalization predicts. We find, for all U.S. exchange-listed common stocks from 1988 to 2010,[46] that inclusion in the DJIA, over and above its size, significantly reduces the efficiency of the market for its stock. Over and above the market capitalization considerations detailed above, therefore, our research does not support a consideration that inclusion in a major index facilitates a finding of market efficiency.

We also find that, *ceteris paribus*, the market for:

- An NYSE stock is significantly less efficient than that for a hypothetical Nasdaq stock without a market maker.
- An AMEX stock is significantly more efficient than that for a hypothetical Nasdaq stock without a market maker.
- A stock listed on another US exchange (such as Boston) is insignificantly less efficient than that for a hypothetical Nasdaq stock without a market maker.
- A stock in 1990, 1991, or 1992 is less efficient than that in other years.

It should be noted that these results are robust to alterations in the statistical model. We performed sensitivity analyses with a) *ex post* arbitrage risk, b) sign constraints on the correlations of returns in the determination of legs of the arbitrage portfolio, c) sign constraints on the hedge ratios, d) number of legs in the arbitrage portfolio, and e) the risk-free rate. The empirical findings are qualitatively the same as for the baseline regressions.

V. Conclusions

We discuss arbitrage risk, a negative proxy for market efficiency based on financial economics, and show how it can be applied to securities class actions. We calculate market efficiency percentiles for all U.S. exchange-listed common stocks from 1988 to 2010.

[46] Restrictions are detailed at the beginning of Section 4.

We also test the dependence of arbitrage risk on various standard factors used by courts in the determination of market efficiency. Some of these empirical findings do not seem consistent with "conventional wisdom"—as Warren Buffett is famously supposed to have said, "Well, it may be all right in practice, but it will never work in theory." However, we show that our empirical findings are actually consistent with economic theory.

We derive structural models of trading volume and market efficiency in a separate paper.[47] We use the panel nature of the data to identify appropriate instruments for the proxy variables and for the endogenous variables. Using idiosyncratic risk, *ex ante* arbitrage risk and *ex post* arbitrage risk as separate (negative) proxies for market efficiency, we estimate these structural models, separately for all Nasdaq and all non-Nasdaq U.S. exchange-listed common stocks, for 2001 to 2010.

The list of determinants of market efficiency considered in this paper is not exhaustive. Academic research and interviews with financial practitioners have suggested additional factors such as external and internal regulations, and industrial organization (including supply and demand structures) of product markets. We intend to utilize data on industry codes, and industry properties such as pricing and concentration, to analyze these additional factors affecting market efficiency.

Cammer Factor (5)—the cause-and-effect relationship between material disclosures and changes in the security's price—is typically analyzed using event studies, which are joint tests of market efficiency and significance of particular events.[48] Using summaries of such event studies as proxies for market efficiency in the context of a macro-analysis like ours would be possible only with substantial simplifications/assumptions such as restricting our attention to earnings announcements different from consensus analyst forecasts as the only surprises for a stock. We intend to undertake such an analysis in the future.

Finally, we propose to investigate alternative proxies for market efficiency, such as put-call parity of options on the security of interest.

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[47] Rajeev Bhattacharya, "Structural Models of Market Efficiency," *Mimeo* (2012).

[48] See, e.g., John Campbell, Andrew Lo, and A. Craig MacKinlay, *The Econometrics of Financial Markets,* Princeton University Press, Princeton, NJ (1997); and Jeffrey Pontiff, "Costly arbitrage and the myth of idiosyncratic risk," *Journal of Accounting and Economics* (2006).

Appendix 1: Number of Unique Stock-Year Combinations

Year	All	With Unique PERMNO, Ticker, and CUSIP in Calendar Year	With Calendar Year Trading Restrictions	After Mergers with Other Data
All Years	141,591	131,779	106,585	37,111
1988	5,323	4,839	4,040	538
1989	4,980	4,633	4,053	578
1990	4,772	4,454	3,923	585
1991	4,843	4,523	3,901	610
1992	6,434	5,973	4,669	652
1993	6,976	6,450	4,911	754
1994	7,367	6,871	5,160	866
1995	7,757	7,170	5,507	990
1996	8,282	7,606	5,605	1,098
1997	8,468	7,710	5,781	1,237
1998	8,254	7,544	5,869	1,415
1999	7,917	7,218	5,551	1,542
2000	7,528	6,835	5,198	1,646
2001	6,692	6,252	5,016	1,765
2002	5,955	5,56 2	4,850	1,917
2003	5,497	5,231	4,535	2,034
2004	5,286	5,032	4,314	2,185
2005	5,228	4,976	4,162	2,379
2006	5,179	4,893	4,085	2,619
2007	5,155	4,891	3,993	2,859
2008	4,843	4,591	3,923	2,900
2009	4,533	4,343	3,871	3,040
2010	4,322	4,182	3,668	2,902

Appendix 2: Summary Statistics

Year	Arbitrage Risk		Turnover		Number of Analysts		Number of Nasdaq Market Makers		Log of Market Capitalization		Bid-Ask Spread		Public Float Ratio		Institutional Ownership Ratio		Serial Correlation		Explanatory Power	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
All	3.97%	9.28%	0.75%	0.86%	11.8	11.3	16.3	20.0	13.21	1.87	1.37%	2.30%	98.01%	16.27%	56.65%	29.18%	-16.83%	15.71%	16.96%	16.23%
1988	2.85%	1.74%	0.28%	0.33%	13.2	12.2	5.2	9.2	12.63	1.80	4.22%	4.49%	97.43%	12.97%	37.92%	19.18%	-14.52%	15.23%	14.62%	16.00%
1989	3.49%	3.11%	0.30%	0.30%	14.3	13.1	5.9	10.0	12.66	1.89	3.76%	3.10%	97.73%	8.51%	38.35%	20.11%	-13.87%	15.34%	10.64%	12.95%
1990	7.21%	10.73%	0.28%	0.27%	11.9	10.6	5.6	9.8	12.60	1.95	5.46%	5.31%	98.33%	8.04%	39.58%	20.82%	-13.08%	15.09%	12.94%	13.55%
1991	39.66%	58.20%	0.34%	0.37%	10.7	9.7	5.4	9.6	12.72	1.93	6.05%	8.49%	96.51%	18.65%	42.78%	21.64%	-15.56%	15.65%	10.48%	10.70%
1992	7.25%	11.99%	0.35%	0.36%	10.7	9.8	5.9	10.1	12.92	1.89	2.99%	4.85%	95.05%	29.43%	44.97%	22.45%	-14.36%	15.13%	6.27%	7.30%
1993	2.73%	1.60%	0.40%	0.46%	11.8	11.1	6.4	10.2	12.91	1.86	2.75%	2.53%	96.27%	35.65%	44.81%	22.55%	-14.34%	15.47%	4.59%	5.46%
1994	2.78%	1.81%	0.40%	0.50%	12.4	12.4	6.9	10.3	12.80	1.89	3.10%	3.42%	95.18%	41.80%	44.38%	23.79%	-13.73%	15.73%	6.49%	7.00%
1995	2.83%	2.00%	0.49%	0.61%	12.5	13.2	7.0	10.1	12.80	1.91	3.17%	3.71%	94.73%	41.66%	44.14%	24.87%	-12.93%	14.86%	3.74%	4.58%
1996	2.91%	1.76%	0.51%	0.57%	12.2	12.6	6.8	9.3	12.90	1.89	2.86%	2.47%	96.86%	13.73%	43.99%	24.86%	-14.27%	15.22%	6.39%	8.12%
1997	3.01%	1.76%	0.54%	0.66%	12.0	12.4	7.6	10.1	12.99	1.90	2.56%	2.51%	97.31%	15.35%	45.83%	25.92%	-14.07%	15.13%	9.13%	11.01%
1998	3.49%	2.08%	0.52%	0.58%	11.4	11.8	9.8	12.3	13.03	1.91	2.39%	2.07%	97.01%	35.48%	46.61%	25.34%	-15.30%	15.76%	11.26%	10.61%
1999	3.72%	2.00%	0.57%	0.71%	11.8	12.0	10.7	13.7	13.01	1.94	2.52%	2.52%	97.84%	25.76%	47.60%	26.70%	-15.68%	15.57%	4.27%	6.65%
2000	4.45%	2.37%	0.71%	0.87%	11.7	12.0	12.1	15.8	13.15	1.97	2.38%	2.44%	98.54%	6.24%	48.23%	27.05%	-15.17%	15.50%	7.31%	7.61%
2001	3.93%	2.36%	0.66%	0.79%	11.6	11.4	14.3	18.2	13.22	1.92	1.58%	1.65%	98.62%	4.77%	51.89%	27.61%	-17.11%	15.98%	13.09%	12.36%
2002	3.54%	2.08%	0.68%	0.80%	11.4	11.2	16.5	20.0	13.19	1.86	1.28%	1.39%	98.44%	8.64%	54.16%	27.61%	-15.80%	15.54%	19.15%	15.49%
2003	2.73%	1.67%	0.73%	0.85%	11.7	11.8	16.6	20.2	13.28	1.80	0.71%	0.88%	97.76%	15.11%	56.73%	28.18%	-18.39%	15.86%	17.12%	14.60%
2004	2.37%	1.30%	0.80%	1.24%	11.3	10.7	18.3	21.1	13.51	1.72	0.41%	0.59%	98.33%	5.62%	61.43%	28.61%	-17.04%	15.59%	16.15%	11.30%
2005	2.27%	1.23%	0.80%	0.93%	11.2	10.4	20.3	22.4	13.53	1.76	0.39%	0.58%	98.37%	9.15%	63.50%	29.50%	-18.80%	15.59%	15.63%	12.39%
2006	2.24%	1.17%	0.86%	0.77%	11.6	10.4	21.4	22.5	13.58	1.75	0.31%	0.45%	98.47%	6.43%	65.50%	29.18%	-19.33%	15.53%	16.16%	12.18%
2007	2.70%	1.45%	1.00%	0.90%	11.6	10.2	21.8	21.8	13.58	1.78	0.38%	0.59%	98.50%	5.43%	69.55%	30.44%	-18.65%	15.81%	19.83%	14.94%
2008	4.45%	2.68%	1.13%	0.96%	11.7	10.5	22.6	22.1	13.28	1.85	0.95%	1.71%	98.81%	4.63%	67.85%	30.03%	-16.42%	15.65%	30.29%	19.04%
2009	4.77%	2.70%	1.02%	0.98%	11.6	11.1	23.3	22.3	13.00	1.88	0.97%	1.82%	98.78%	5.28%	62.50%	28.80%	-18.04%	15.87%	29.39%	18.87%
2010	2.57%	1.49%	0.95%	0.91%	12.9	12.0	24.0	23.4	13.37	1.85	0.47%	0.89%	98.99%	3.70%	64.93%	28.74%	-19.53%	15.47%	30.44%	18.50%

Appendix 3: Summary Regression Results

Number of Observations Read	37,111
Number of Observations Used	35,587
Number of Observations with Missing Values	1,524

Source	Degrees of Freedom	Sum of Squares (SS)	Mean SS	F-Statistic	p-Value
Model	36	93.1478	2.58744	851.3	<0.0001
Error	35,551	108.0536	0.00304		
Uncorrected Total	35,587	201.2014			

R^2	0.463
Adjusted R^2	0.462