

The Innovation Arms Race*

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Abstract

Economists have long recognized that competition and innovation interact as key drivers of economic growth (Schumpeter, 1943; Arrow, 1962; Aghion and Howitt, 1992). Acknowledging this, regulators carefully scrutinize competitive behaviors that potentially affect innovation incentives, in particular in the case of proposed mergers (Shapiro, 2012). Do acquisitions of innovative targets spur or stifle innovation? To address this question, we provide a first large scale empirical investigation of M&A effects on acquirer rivals' incentives to innovate and the equilibrium outcome resulting from this competitive process. Our results are consistent with an innovation arms race: acquisitions of innovative targets push acquirer rivals to invest more in innovation, both internally through research and development (R&D) and externally through acquisition of innovative targets, and this increase in innovation investment necessary to maintain competitive position leads to a decrease in firm market valuation. These results are robust to endogeneity and are driven by the High-Technology industry. This arms race process appears stronger for leaders and neck-and-neck firms. Initial patents and patent citations based evidence shows no sign of innovation investment efficiency decline, suggesting that the innovation arms race generates a transfer of economic rent favorable to consumers.

Keywords: competition, innovation, mergers and acquisitions

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“Managements are forced by market pressures to support innovation activity systematically and substantially, and success of the efforts of any one business firm forces its rivals to step up their own efforts. The result is a ferocious arms race among the firms in the most rapidly evolving sectors of the economy, with innovation as the prime weapon”

(Baumol, 2002)

1. Introduction

Baumol (2002) argues that the innovation engine is the core feature of modern capitalism, fueling exponential economic growth for two centuries. According to the author, the innovation engine is fed by a mixture of oligopolistic competition, innovation routinization, sharing and licensing, and fierce arms races between rivals. But such an arms race implies value-loss at the firm level and rent transfers to consumers—is that the correct characterization of the side-effects of competitive innovation?

The question is of importance, as attested by regulatory agencies in charge of competition supervision activities. Typically, innovation ripple effects are analyzed when reviewing specific merger and acquisition (M&A) cases (Shapiro, 2012). In particular, the 2010 release of the Horizontal Merger Guidelines issued by the U.S. Department of Justice and Federal Trade Commission (DOJ/FTC)¹ dedicates Section 6.4 to the analysis of unilateral effects on innovation and product variety. However, competition and innovation maintain complex interactions (Schumpeter, 1943; Arrow, 1962; Aghion and Howitt, 1992). Whether the innovation arms race faithfully depicts competition among rivals, leading to these fierce fights, is an empirical question.

Game theory provides the necessary theoretical foundation to study equilibrium outcomes of escalating competitive situations in which each party focuses on out-doing the others within an arms race game, initially introduced to study competition among countries. In a non-cooperative situation, each player’s dominant strategy is to choose the “high” action and the resulting Nash equilibrium is worse for everyone than if they had chosen “low” action (Osborne, 2003). Theory therefore provides clear and unambiguous predictions to test the Arms Race Hypothesis: (i) firms will invest more in innovation in response to rivals’ investments in innovation (the *correlated investments* prediction) and (ii) the resulting outcome will be value destroying for the parties in competition, consistent with either a decline in

¹ <https://www.ftc.gov/public-statements/2010/08/horizontal-merger-guidelines-united-states-department-justice-federal>

innovation investment efficiency or a transfer of rents beneficial to consumers (the *value decrease* prediction). Interestingly, the combination of these two predictions identifies the *Arms Race Hypothesis* as an alternative to the classic Schumpeter (1943) *Rent Dissipation Hypothesis* (that implies less investment in innovation in response to an increase in competitive pressure, not more) and Arrow's (1962) *Competition Escape Hypothesis* (that implies a non value destroying, if not value creating, effect of firm investments in response to an increase in competitive pressure), as summarized in Figure 1. Our empirical strategy is designed to confront the Arms Race, the Schumpeter Rent Dissipation and Arrow Competition Escape hypothesis predictions with the facts.

The Google versus Microsoft fight in the on-line advertising industry is a typical example of the economic mechanism that we are studying. In early 2007, Google and Microsoft fought fiercely to acquire DoubleClick, a major player specialized in search based online advertising. Google won, paying \$3.1 billion, the transaction becoming Google's largest since its initial public offering. Microsoft was left with few alternatives and rushed to acquire aQuantive in May of the same year, paying \$6 billion (the correlated investment prediction), representing a hefty 85% bid premium. Being unable to catch up with Google in the online search race, Microsoft finally announced a \$6.2 billion writedown on July 2, 2012 (the value decrease prediction). Apparently, the aQuantive acquisition did not pay off. The Google versus Microsoft battle did not stop there, as witnessed by Microsoft's attempt to acquire Yahoo in February 2008 (Aktas et al., 2013), with a \$43.7 billion offer (rebuffed by Yahoo). We investigate whether such dramatic arms races between rivals are at play on a regular basis in the U.S. economy.

While a large body of literature on innovation has developed in financial economics, only a limited number of recent contributions focus explicitly on interactions between M&A and innovation. Lerner, et al. (2011) show that leveraged buyouts do not reduce innovation at portfolio companies. Atanassov (2013) asks whether the threat of hostile takeovers stifles innovation and reports results inconsistent with such claim. Phillips and Zhdanov (2013) suggest that large firms, by their acquisitions, provide incentives to small firms to invest in innovation to become attractive targets and this task sharing could be socially efficient. Bena and Li (2014) investigate interactions between M&A and innovation and report that innovative firms are more likely to engage in M&A, that technological overlap between the merging parties increases the probability of a match, and that innovation-driven acquisitions create more value in the long run. Chen et al. (2016) adopt a different perspective and study the role of envy (generated by innovation awards obtained by rivals) in the willingness to make acquisitions. Their results suggest that behavioral factors play a role. Cunningham et al. (2020), studying the pharmaceutical industry, argue that acquisitions may be motivated by the willingness to kill potential innovation by rivals. In a similar vein,

Kamepalli et al. (2020) study the impact of high-priced acquisitions of entrants by incumbents on incentives to innovate and argue that such acquisitions do not necessarily stimulate innovation. Matray (2021) documents local innovation spillovers from listed firms to private firms at short distances, stemming from knowledge diffusion. None of these contributions focus specifically on the effects of acquisitions on acquirer rivals' incentives to innovate and the resulting outcomes of this competitive process. This is our main endeavor.

Our study covers the period 1996 to 2019, constrained by the coverage of the Thomson Reuters (now Refinitiv) SDC database and the availability of the Hoberg and Phillips (2010) (HP henceforth) similarity scores. We follow all firms listed on the New-York Stock Exchange (NYSE), National Association of Securities Dealers Automated Quotations (NASDAQ), and American Stock Exchange (AMEX) during that period, excluding financial institutions (Standard Industrial Classification (SIC) codes 6,000 to 6,999) because of the lack of data on innovation. We collect M&A transactions in the SDC database. We include both horizontal and non-horizontal transactions because the definition of horizontal transactions is subject to industry classification limitations (Bhojra et al., 2003) and because M&A effects on acquirer rivals' incentives to innovate may not be limited to within industry transactions. We also keep acquisitions of unlisted targets in our sample because these firms are important sources of innovation (Gao et al., 2018). Our M&A sample includes 46,418 transactions by 6,413 unique acquirers.

Firms can invest in innovation organically by spending more on research and development (R&D) and externally by buying innovative targets. These will be the dependent variables used to test the correlated investment prediction. These variables are innovation inputs and should, therefore, capture firms' intention to react to rivals' moves. Capturing value effects of innovation investments to test the value decrease prediction is challenging because cash-flow consequences of these investments may take years before they materialize. Instead of relying on some operational performance measure, we follow Bloom et al. (2013) and select a market based measure of valuation. Stock prices react to the capitalized value of cash-flow consequences of investment decisions as soon as the information is available to investors. The anticipatory nature of the market-based value should therefore allow us to capture valuation effect of innovation investments. We borrow the firm valuation equation from Fama and French (1998). Our variable of interest is a measure of intensity of innovative acquisitions (denoted IA) by firm rivals². We start by identifying innovative targets, whether public or private, in our M&A sample using R&D investment intensity in their 3-digit SIC industry. Next we compute our measure of innovative target

² Our baseline results rest on a count-based measure and we report corresponding value-based results in the Internet Appendix.

acquisition intensity by the ten closest rivals in the product market space (rivals' IA henceforth). To test the Arms Race Hypothesis correlated investment prediction, we regress the firm's R&D (the R&D equation) and IA intensity (the IA equation) on this measure of rivals' IA. Testing the second Arms Race Hypothesis prediction (the value decrease prediction) entails studying the value effect of these investments. We do so by regressing the logarithm of one plus the difference between the market value and book value of total assets scaled by the book value of total assets ($\ln\text{MTBA}$) on firm excess investments (defined as the difference between the current year investment and the three year historical average) in R&D and IA in response to rivals' IA. This test assumes that investors have not (fully) anticipated the start of an arms race process, an assumption that we confront with the data. Our baseline analyses are performed at the intensive margin, keeping only firms whose rivals did perform acquisitions, to avoid producing results driven by firms never exposed to such rivals' moves, and we report results at the extensive margin as a robustness check. Our regressions include firm and year fixed effects as well as time-varying covariates.

It is clearly apparent that R&D and innovative acquisitions are interdependent decisions. We control for this source of simultaneity bias potentially affecting our test of the correlated investment prediction using the conditional mean independence theorem (Stock and Watson, 2020). Because we perform a peer effect analysis (rivals are peers of the firm under focus and therefore subject to the same latent factors), we lag by one year our measure of IA by 10NN rivals to use a predetermined independent variable, which is one way to cure this source of endogeneity (Angrist and Pischke, 2009). However, latent factors that we are concerned with can be persistent through time, reducing the effectiveness of our lagging strategy. Therefore, we check the robustness of our correlated investment prediction test with an instrumental variable approach. Specifically, as in Homberg and Matray (2018), we use the U.S. R&D tax credits program implemented at the state level from 1982 to 2006 as an exogenous shock to incentives to allocate resources to internal innovation, at the expense of external innovation through acquisitions.

Our main results are clear: (i) firms react to an increase in their rivals' innovative acquisitions by investing more in innovation, both organically (R&D) and externally (IA), and (ii) these investments made under pressure from rivals' innovative acquisitions are negatively correlated with market valuation ($\ln\text{MTBA}$). Taken together, these results support the Arms Race Hypothesis. Moreover, the economic effects are sizeable.

More specifically, when we use a specification that controls for firm fixed effects, year fixed effects, time varying control variables (return on assets (ROA henceforth), leverage, cash, intangibility and equity market to book (MTB henceforth) ratios) to the test of the correlated investment prediction, we find a

positive and highly significant (p-values on the order of 0.1%) coefficient on one-year lagged rivals' innovative acquisitions in both the R&D and the IA equations. The economic effects are sizeable: a one standard deviation increase in rivals' IA (count based) increases R&D by 4.3% and IA by 49.16% with respect to their unconditional averages. We obtain comparable results working at the extensive margins (including all firms, whether or not their rivals did undertake IA), as well as when limiting our M&A sample to change of control transactions, or when limiting to horizontal transactions (the acquirer and the target share the same 3-digit SIC code). However, if we limit our M&A sample to public target acquisitions, results are only partially consistent with the correlated investment prediction. This emphasizes the importance of taking into account small private targets to capture IA effects. Results obtained using our instrument and a two-stage least square estimator (2SLS) confirm that a causal interpretation of the correlated investment prediction results is warranted. Using a value-based measure of intensity of innovative acquisitions by firm rivals does not alter these conclusions.

Market value regressions that test the Arms Race's value decrease prediction display negative and statistically significant coefficients for the interaction terms between rival IA investments and firm excess R&D and excess IA³. These results are obtained controlling again for firm fixed effects, year fixed effects and time varying control variables included in the Fama and French (1998) market valuation equation. Economic effects are smaller than in the case of the correlated investment prediction test but remain sizeable, with a value loss of 2.5% under the combined effect of an one standard deviation increase of rival IA (count based) and excess R&D or excess IA.

Results obtained so far prove moreover to be robust to many alternative specifications, in particular the addition of industry times year fixed effects to control for industry level time-varying latent factors such as industry competition, concentration, growth opportunities or technological shocks, an alternative measure of rival IA using as the denominator aggregate rivals' total assets to avoid our results to be driven by rivals' acquisitions themselves, and multiple imputations of missing R&D values collected in Compustat as argued in Koh et al. (2021).

We next replicate our results by sector, using the Fama and French five industries classification⁴. The High-Technology, and to some extent the health (pharma) sectors are driving our results. This makes sense: an innovation arms race will occur in equilibrium if market conditions are such that there are enough incentives for rivals to invest in innovation, and both High-Technology and pharmaceuticals satisfy these conditions as innovation intensive.

³ Results statistically significant at 1% or 5% level of confidence, depending on the specification.

⁴ Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

We also perform within-industry investigations. We start by distinguishing industry leaders and laggards (firms above and below both the industry median ROA and market share, respectively). We anticipate that industry leaders are more likely to react to competitive pressure by investing more in innovation while industry laggards may be too financially constrained to follow this strategy (these arguments ground partially the Schumpeter (1943) rent dissipation and Arrow (1962) competition escape hypotheses⁵). Our results only partially support these predictions: industry leaders and laggards both react to rivals' IA by investing more in R&D and IA but industry leaders invest significantly more in IA than industry laggards. Excess investment in R&D and IA by industry leaders negatively impacts firm market value, consistent with the Arms Race value decrease prediction. Aghion et al. (2005) argue that the relation between competition and innovation follows an inverted U shape, with neck-and-neck firms (firms in fierce competition against close rivals) having the highest incentives to invest in innovation. We follow Chen and Wu (2019) and use HP similarity scores to identify firm and neck-and-neck competition. Our results reveal that neck-and-neck firms are displaying a stronger R&D investment and IA reactions to rivals' IA and that this behavior appears to be more value decreasing for IA.

We finally investigate whether the loss of value generated by the Arms Race mechanism finds its roots in a decline in innovation efficiency or a transfer of rents beneficial to the consumer. Using the NBER Patent Citations data file (Hall et al., 2001) and measuring innovation output as the logarithm of the three years forward cumulated number of patents or patent citations, we don't find evidence of a decrease in innovation efficiency. Thus, this preliminary investigation appears to support a transfer of rents to the consumers, an outcome that should be part of regulatory authorities' analyses.

Our contribution to the M&A regulation debate is twofold: the broad picture is that M&As spur investment in innovation but without increasing incumbents' rents, due to the arms race equilibrium outcome of this process. Our industry level and within-industry results emphasize the actual effect of any given M&A transaction on acquirer rivals' incentives to innovate is context dependent. Industry characteristics and the competitive position of involved industry players are important determinants here. Beyond this contribution to the M&A regulation debate, our results highlight the importance of firm interactions in shaping investment decisions in innovation, one more form of peer effects (eg. Foucault and Frésard, 2014; Bustamante and Frésard, 2020). Our results are also informative on the choice between organic and external innovative growth, showing the conditions under which these materialize in response to competitive pressure. Finally, given the scale and scope of acquisition activity, the analysis

⁵ The anticipation of lower benefits from innovation leading to less innovation is another channel through which the Schumpeter (1943) rent dissipation hypothesis may be at work.

of how rivals' acquisitions impact a firm's innovation incentives have implications for the broader literature on the determinants of innovation.

We summarize the relevant literature in Section 2. Section 3 is dedicated to our empirical design and Section 4 to our main results. Robustness checks are summarized in Section 5, before we conclude.

2. Literature Review

2.1. Innovation in the Economic and Finance Literature

Innovation's role in economic growth makes it a research topic of first order importance and it has attracted significant attention. The academic literature is vast and giving a fair account of it is beyond the scope of this literature review. We will mention just two examples, representative of the key issues at stake. Romer (1990) develops a model of monopolistic competition that recognizes the endogenous nature of technological changes and its specificities (in particular, the one-time fixed costs of development with no cost of reuse). Aghion and Howitt (1992) incorporate technological obsolescence as a negative externality of innovation in their study of the relation between innovation and economic growth. The authors conclude that a *laissez-faire* policy (letting firms choose frequency and size of innovation) leads to too low economic growth. Unsurprisingly, innovation has also been actively studied in the management literature but the field is again too broad to be summarized here. A representative example is Knott (2008). In short, the author studies whether R&D efficiency is born (organizational IQ) or made (absorptive capacity). Using a large panel of U.S. industries over the 1981 to 2000 period and measuring innovation efficiency as elasticity from a Cobb-Douglas production function, the author concludes that organizational IQ dominates absorptive capacity.

The finance literature has followed this trend. Investigated questions bear on the relation between firm organizational form and innovation, the profile of innovators, and market valuation of innovation among others. Fulghieri and Sevilir (2009) study the impact of competition on the organization of innovation activities within the firm and its financing. Their theoretical analyses conclude that it is optimal for firms subject to competition shocks to choose external organizational structures, in collaboration with specialized start-ups, to hasten product innovation. Seru (2014) reports that single segment firms generate more patents and citations than multi-segments firms. The author concludes that the relation is causal, addressing endogeneity using failed M&A attempts and a difference-in-differences identification strategy. Hirshleifer et al. (2012) take a behavioral approach and study the relation between CEO personality (overconfidence, using the Malmendier and Tate (2008) option-exercise based proxy of

overconfidence, as well as press-based ones) and innovation. They conclude that overconfident CEOs more aggressively pursue innovation but that this does not necessarily create more value for shareholders. Cohen et al. (2013), and Hirshleifer et al. (2013, 2017) uncover systematic stock market misvaluation of innovation activities. In Cohen et al. (2013), the authors show that, while successful R&D investment is to some extent predictable, investors seem to ignore this source of public information and that building a long-short trading strategy around this systematic source of pricing errors is valuable. Hirshleifer et al. (2013, 2017) show that innovation efficiency and originality are strong predictors of future stock returns.

2.2. Innovation and Competition

Schumpeter (1943) introduces two channels through which competition affects innovation: the Rent Dissipation hypothesis (increasing competition leads to a transfer of rents from producers to consumers, pressuring firms to cut investments) and the Creative Destruction one (new technologies replace existing ones).. Arrow (1962) argues on the contrary that, under the pressure of competition, firms invest more aggressively in innovation to differentiate their products from competitors' ones and to better serve consumers (the Competition Escape hypothesis). Recently, the Competition Escape hypothesis has received some empirical support in Hoberg and Phillips (2016) whose results based on Security Exchange Commission (SEC) 10K filings product descriptions lend support to endogenous product differentiation. To some extent, the Competition Escape hypothesis also grounds the contribution of Hombert and Matray (2018). The authors study whether more innovative U.S. manufacturing industries better resist the pressure of import competition from China. Controlling carefully for endogeneity, their results confirm that this is the case. Aghion et al. (2005) argue that the relation between competition and innovation should exhibit an inverted-U shape. Firms in close competition (called neck-and-neck firms) have the strongest incentives to innovate to escape from rivals' pressure because pre-innovation rents are more strongly reduced by an increase in product market competition. Laggard firms will suffer too much from an increase in competition to invest more in innovation while leader ones are shielded enough and don't invest in such a strategy. The authors report consistent empirical evidence on a U.K. panel data set over the period 1973 to 1994.

Another channel through which competition affects innovation is spillover effects among rival firms. Jaffe (1986) focuses on technological spillovers. The position of firms in the technological space is captured thanks to the use of a patent database. Using a sample of 432 firms and data collected over two periods (1972 to 1974 and 1978 to 1980), the author reports a positive spillover effect of rivals' investments in

R&D on R&D productivity (measured by the ratio of patents per dollar investment in R&D), especially for high R&D firms, but mixed evidence for profit and market value spillovers (positive for high R&D firms and negative for low R&D firms). Bloom et al. (2013, 2017) disentangle the business spillover effect from the technological one. As in Jaffe (1986), technological spillover is based on the firm position in the technological space while business spillover weights rivals' R&D by distances in the product space using 4-digit SIC codes. While technological spillover is about knowledge sharing, as in Jaffe (1986), a socially beneficial outcome, business spillover is introduced by the authors as a competitive mechanism by which firms are damaged by loss of market share. The authors use tax-induced changes of R&D capital user cost to address endogeneity issues and report that the technological spillover effect dominates the business one. Matray (2021) focuses on local spillovers of innovation activities. Using a carefully designed identification strategy grounded on staggered adoption of business combination laws in individual U.S. states, the author reports the presence of a causal effect of innovation activities by listed firms on innovation activities by private firms at short distances due to knowledge diffusion.

2.3. Innovation and M&As

The literature has long recognized the risk that financial pressure induces short-termism and that this hampers innovation (see e.g. Stein, 1989, Holmstrom, 1989). Atanassov (2013) explores whether this applies to hostile takeovers. His results come from the analysis of a large sample of listed U.S. firms over the period 1976 to 2000, using business combination anti-takeover laws as exogenous shocks to the probability of hostile takeovers and a difference-in-differences approach as identification strategy. The author reports that innovation declines in the wake of business combination laws enactment and that this negative relation is mitigated in the presence of alternative governance mechanisms (large shareholders, leverage and product market competition in particular), results that are inconsistent with the threat of hostile acquisitions stifling innovation. Phillips and Zhdanov (2013) go one step farther. Their theoretical analysis, corroborated by empirical results, concludes that it may be optimal for large firms to acquire innovation in place of developing it internally. By doing so, these large firms provide incentives to small firms to invest more in innovation, the possibility of being acquired at a large premium acting as a strong stimulus. This incentive-based mechanism generates a positive relation between the intensity of the M&A activity and innovation in the economy, a socially desirable outcome. Recently, Kamepalli et al. (2020) challenge this view, arguing that highly priced acquisitions of new entrants by incumbents may reduce incentives to innovate in industries where customers face switching costs and benefit from network externalities.

Bena and Li (2014) focus on asset complementarities to study the motives and outcomes of acquisitions under the lens of innovation. Asset complementarity is measured by the technological overlap between merging parties (in particular, patent cross-citations and common knowledge base). Studying the 1984 to 2006 period, the authors report that more innovative firms are more likely to engage in acquisitions, that the degree of technological overlap increases the probability of merger and that innovation-driven acquisitions achieve better long-term real outcomes in terms of innovation output, operating and market-based performance.

Chen et al. (2016) adopt a behavioral perspective to study motivations to engage in the M&A market. The authors take the case of innovation awards granted by the R&D Magazine from 1965 to 2015, presented as the *Oscar of Innovation*, and use state-level trade-secret law adoptions under the Uniform Trade Secrets Act to break endogeneity. Results confirm that the propensity to acquire increases following R&D awards won by competitors, that this effect is magnified in the absence of financial constraints, by stronger technology competition and with more overconfident CEOs. Moreover, acquirers focus on more innovative targets.

The relation between M&A and innovation is also certainly industry specific. Cunningham et al. (2020) focus on the pharmaceutical industry. Making use of very granular data on product and patent characteristics, the authors uncover strategies designed by incumbent firms to kill potentially threatening innovations by acquiring rivals in their early life cycle stage and stopping the development of new drugs. Haucap et al. (2019) develop a model interacting M&As and product innovation and test their prediction on a sample of European transactions also in the pharmaceutical industry, using a differences-in-differences specification as identification strategy. They report that average patenting and R&D of the merged entity and its rivals decline substantially in post-merger periods. Cunningham et al. (2020) and Haucap et al. (2019) results suggest that in the pharmaceutical industry, M&A transactions negatively impact innovation.

To summarize, the literature on innovation is vast and addresses essential questions such as economic growth, competition, and business strategies. Consequently, regulatory agencies in charge of competition supervision have increasingly incorporated side-effects on innovation incentives in their investigations (Shapiro, 2012). To the best of our knowledge, the Arms Race hypothesis has not been tested as such. As explained in introduction and clearly apparent in Figure 1, it generates two predictions (correlated investments and value decrease) that, taken together, allow us to differentiate it from the Schumpeter (1943) Rent Dissipation and Arrow (1962) Competition Escape hypotheses.

3. Data and Empirical Design

3.1. Data

We use all NYSE, NASDAQ, and AMEX firms for which the necessary information can be collected in the Compustat and CRSP (Center for Research in Security Prices) databases, excluding financial institutions (SIC codes 6,000 to 6,999). Few financial institutions report R&D and/or patents because their research activities do not meet the necessary criteria to do so (Frame and White, 2004). Our period of analysis is constrained by data coverage in the SDC M&A database, significantly expanded from 1992, the availability of product similarity scores provided in the HP dataset⁶ that starts in 1989 and ends in 2019 and the requirement of three years of historical data to compute excess R&D and excess IA (see Equations 2 and 4). M&A transactions are matched to firm-year data with one year lag to avoid any forward looking bias. We therefore start in 1996 and end in 2019.

We select all completed M&A transactions from the SDC database during that time period and keep public, private, and subsidiary targets. Transactions with missing transaction values are also included in our sample (they account for 46.51% of the transactions, and disproportionately represent private targets). Our sample contains 46,418 transactions, among which are 838 acquisitions of certain assets, 1,584 acquisitions of majority interests, 3,923 acquisition of partial interests, 659 acquisitions of remaining interests, 29,863 acquisitions, and 9,537 mergers according to the SDC deal forms classification. We do not require a minimum percentage to be acquired (85.32% of acquisitions in our sample are full acquisitions). Note that we include both horizontal and non-horizontal transactions because the definition of horizontal transactions is subject to industry classification limitations (Bhojra et al., 2003) and because M&A effects on acquirer rivals' incentives to innovate may not be limited to within industry transactions. We also keep acquisitions of unlisted targets in our sample because these firms are important contributors of innovation (Gao et al., 2018).

Table 1 tabulates our M&A sample through time. Columns 2 and 3 report the number of acquisitions and aggregate deal values. clearly apparent is the well-known wave pattern displayed by aggregate M&A activity, with the peak observed at the end of nineties, the rebound of the market in between the Internet bubble burst and the 2008 financial crisis, and its restart during the last decade (Alexandridis, 2017). Table 1 Column 1 provides the corresponding number of unique acquirers. The activity of repetitive acquirers is

⁶ Available at <http://hobergphillips.tuck.dartmouth.edu/industryclass.htm>.

clearly apparent: our 46,418 M&A transactions are undertaken by 6,413 unique firms, confirming previous findings (e.g.: Fuller et al., 2001). Comparing the corresponding cells in Columns 1 (the number of unique acquirers by year) and 2 (the number of acquisitions), it appears that, on average, acquirers undertake approximately two acquisitions per year.

3.2. Variables

Dependent Variable

To test the Arms Race's correlated investment prediction, we select dependent variables that capture firm investment in innovation (in a classic revealed preferences approach). But measuring investments in innovation is challenging. Granja and Moreira (2019) is one of the very rare papers working at the product level, using barcodes information collected in the Nielsen Retail Measurement Services scanner dataset (Kilts-Nielsen Data Center at the University of Chicago Booth School of Business). This database provides highly valuable product level information but is limited to the consumer goods industry. However, to the best of our knowledge, there is no standardized electronic database that tracks innovation at the product level for a large cohort of firms representative of the U.S. economy in the long run. A first classic firm level measure is R&D, either as a flow (R&D expenses) or a stock (some measure of cumulated R&D expenses, potentially applying a depreciation rate, such in Jaffe (1986), Bloom et al. (2013, 2017) or Hombert and Matray (2018). An R&D-based measure has well-documented shortcomings (not all innovation investments meet the necessary materiality requirements to be accounted for as R&D and R&D is available only for listed firms). However, it is a measure of financial resources committed to innovation within the firm (an innovation input), which is what we want to capture (the intention to innovate). Alternative measures, such patents and patent citations, to the collection of which considerable resources have been dedicated (Hall et al., 2001 and Lerner and Seru, 2017), are measures of innovation output, less suited to our analysis because we are interested in strategic choices: a firm can choose to invest in R&D, but cannot choose to successfully produce a patentable innovation (and further, not all innovations are patented due to fears of disclosing information to competitors). A recent trend is the use of text-based analysis techniques to develop alternative measures of innovation, such as Bellstam et al. (2017) or Bowen et al. (2019). The textual material may come from SEC filings (such as the SEC 10K filings) or from patent applications. These techniques open the doors to broader measures of innovation but are not currently available over long periods for large samples of listed firms. We therefore use R&D expenses divided by total assets (labeled *R&D Intensity* henceforth) as our measure of within-firm investment in innovation.

Innovation investments can alternatively take the form of acquisitions of innovative targets. Acquiring innovation is a major motivation to enter into the M&A market, as documented in numerous academic contributions (e.g.: Phillips and Zhdanov, 2013). Like *R&D Intensity*, this is a measure of innovation input, not (or less) subject to delays like the patenting process, and it complements within firm innovation investment measures to take into account resources allocated to external acquisitions of innovation. Moreover, firm acquisitions can easily be collected over long periods and for large samples thanks to the SDC database. Building our measure of innovative target acquisitions (labelled *Innovative Acquisitions* or IA henceforth) requires us to classify targets as innovative or not. We design a simple procedure, based on the degree of investment in R&D in the target industry, suited to public and private targets and easily replicable. The procedure follows three steps:

- for each year and 3-digit SIC industry, we compute the sum of R&D expenses by all Compustat firms (listed firms, therefore) belonging to this industry according to CRSP historical SIC codes. We next divide the sum of R&D expenses by the sum of total assets of the corresponding firms. This provides us an industry-year measure of R&D intensity;
- in the next step, for each year, we sort 3-digit SIC industries by industry R&D intensity. Innovative industries are industries in the highest quartile of R&D intensity;
- finally, we classify targets as innovative targets when, according to the 3-digit SIC code collected in SDC, they belong to an innovative industry.

This process of identifying the innovative targets allows us to take into account the rise and fall of innovation activities in each industry over time. Importantly, this simple industry-based procedure allows us to classify both listed and unlisted targets and provides us our second dependent variables, IA, defined as the number of innovative target acquisitions divided by the number of acquisitions⁷. Table 1 provides descriptive statistics. Out of 46,418 M&A transactions in our sample, 9,336 target innovative firms (Column 4). This amounts to close to twenty-five percent of the sample, to some extent (but not necessarily) a mechanical consequence of our IA identification procedure (industries are classified as innovative if they rank in the highest quartile by R&D intensity). The percentage of IA is also clearly declining through time, from 24.01% (722 divided by 3,006) in 1996 to 5.43% (62 divided by 1,141) in 2017, a trend most probably due to the high representation of Internet-related companies in mergers at the end of the nineties. It is also noteworthy to compare the sample of all IA (Column 4) to the subset of

⁷ In the absence of an acquisition by the firm-year under focus, IA is set to zero. We also report results with a value based measure of IA in the Internet Appendix, built using deal values reported in SDC, available for roughly half of our M&A sample.

listed ones (Columns 6): these accounts for only 14.16% of the transactions (1,322 divided by 9,336), stressing the importance of private targets inclusion in our sample.

The investigation of the Arms Race value decrease prediction requires some measure of economic rent obtained thanks to innovation investments. The main issue here is that these investments take years to materialize, the patenting process itself introducing long delays (Hall et al., 2001; Lerner and Seru, 2017). Using accounting based performance measures like ROA is therefore problematic because the cash-flows generated by innovation investments will only occur many years after the corresponding investments. This leads us to select a market valuation-based measure as the dependent variable, like Bloom et al. (2013), to test the value decrease prediction: investors react quickly to public information affecting future cash-flows and, under the efficient market hypothesis (Fama, 1991), changes in market value represent the current value of these anticipated cash-flow streams. Changes in market value to firm innovation investments should therefore indicate the value effect, if any, of these investment decisions as perceived by investors. More specifically, we use the logarithm of one plus the market valuation ratio used in Fama and French (1998), which is the difference between the market value and book value of total assets scaled by the book value of total assets, denoted henceforth $\ln MTBA$. The log transform helps to control for the significant skewness of MTBA and allows direct interpretation of coefficients as percentage changes in MTBA of a unit change in the variable of interest.

Table 2 reports descriptive statistics on all variables used in our multivariate analyses. As indicated in Column 6, the number of firm-year observations varies depending on data availability. Panel A is dedicated to variables used to test the correlated investment prediction and Panel B, the value decrease prediction. Variables are grouped into dependent, independent and control variables, so as to clarify their status and clearly identify where endogeneity is potentially an issue. In our sample of 59,568 firm-year observations, R&D expense amounts on average to 4.9% of total assets. Resources allocated to R&D is however highly heterogeneous, with a standard deviation of 9.4%, and right-skewed (the median is a mere 0.3%), witnessing that internal investments in innovation is driven by a sub-sample of R&D intensive firms. These figures are comparable to numbers reported in the extant literature. For example, He and Tian (2013) report that firms' R&D expenses amount to 5% of total assets in their sample of 5,640 firm-year observations over the period 1998 to 2003. Chang et al. (2015) display a comparable 4% average on a sample of 25,860 firm-year observations over the period 1993 to 2005. We also provide in Table 2 the average number of IA by firm-year, which is 0.091. The distribution is again highly right skewed, as the third quartile is still 0. IA are in fact concentrated into the last decile of the distribution (untabulated). The

average lnMTBA is 0.272, a figure that can't be compared to Fama and French (1998) because the authors don't report descriptive statistics.

Independent Variables

To test the Arms Race correlated investment prediction, we are interested in the effect of rival's IA on the subject firm's incentives to innovate. Our variable of interest is therefore a measure of intensity of such acquisitions by firm rivals. We label this measure RICI for Rival Intensity of Innovative Acquisitions – Count Based⁸ and obtain it using the following procedure:

- we start by identifying innovative targets in our M&A sample as described above;
- next, we collect firm rivals. To this end, we use HP similarity scores to obtain, year by year, the portfolio of the firm's 10 nearest neighbors in the product market space (denoted $10NN_t$).
- we count the number of acquisitions by 10NN rivals in year t : $RAC_{it} = \sum_{j \in 10NN_{it}} AC_{ijt}$ where AC_{ijt} is the number of acquisitions by rival j of firm i in year t ;
- we count the number of IA by 10NN rivals in year t : $RIAC_{it} = \sum_{j \in 10NN_{it}} IAC_{ijt}$ where IAC_{ijt} is the number of IA by rival j of firm i in year t ;
- $RICI$ for firm i in year t is finally defined as the ratio of $RIAC_{it}$ to RAC_{it} :

$$RICI_{it} = \frac{RIAC_{it}}{RAC_{it}} \text{ if } RAC_{it} > 0 \text{ and } 0 \text{ otherwise} \quad (1)$$

where i is the firm subscript and t is the year subscript.

RICI depends on the use of HP similarity scores to identify rivals. Similarity scores are refreshed each year based on product descriptions reported in SEC 10-K filings and therefore, our 10NN rivals portfolio compositions are themselves updated every year, providing a dynamic depiction of firms' competitive environment. Moreover, because HP similarity scores are built on product description similarities, identified rivals are firms that produce products most similar to the product portfolio of the firm under focus. This corresponds to concept of the relevant market described in the DOJ/FTC Horizontal Mergers Guidelines. The main limitation of RICI is that it captures only acquisition activities by listed rivals, while

⁸ We develop a similar measure for value-based analyses reported in Appendix under the acronym *RIVI* for Rival Intensity of Innovative Acquisitions – Valued Based.

we know that the M&A market has witnessed a rise in private buyers' activities during the analyzed period (Eckbo et al., 2018).

Table 2, Panel A reports that, on average 18% of 10*NN* rivals' acquisitions are innovative, with a highly right skewed distribution, more than half of the sample undertaking no innovative acquisitions (the median is 0). Indeed, the skewness reflects the fact that innovative acquisitions cluster (consistent with the Arms Race hypothesis), so that conditional on there being one innovative acquisition, on average 48.9% of rival acquisitions are innovative.

The value decrease prediction of the Arms Race hypothesis is a statement on the value effect of firm decisions to make innovative investments (whether as R&D expenses or buying innovative targets) under the pressure of IA by rivals. Therefore, our independent variables of interest will be the interaction of firm innovative investments and RICI. To capture the firm response specific to rivals' pressure, we control for the firm historical innovation investment policy by decomposing the current R&D and IA into the three-year historical R&D and IA averages and the current excess R&D and IA. This procedure generates the historical and excess R&D intensity and IA interactions with RICI, our two independent variables of interest to test the value decrease prediction:

$$RICI_{it} \times R\&D_{it}^{histo} = RICI_{it} \times \left(\frac{1}{3} \sum_{\tau=1}^3 R\&D_{it-\tau}\right) \quad (2)$$

$$RICI_{it} \times IA_{it}^{histo} = RICI_{it} \times \left(\frac{1}{3} \sum_{\tau=1}^3 IA_{it-\tau}\right) \quad (3)$$

$$RICI_{it} \times R\&D_{it}^{excess} = RICI_{it} \times \left(R\&D_{it} - \frac{1}{3} \sum_{\tau=1}^3 R\&D_{it-\tau}\right) \quad (4)$$

$$RICI_{it} \times IA_{it}^{excess} = RICI_{it} \times \left(IA_{it} - \frac{1}{3} \sum_{\tau=1}^3 IA_{it-\tau}\right) \quad (5)$$

where $R\&D_{it}^{excess}$ is the firm i excess R&D intensity in year t , IA_{it}^{excess} , the excess IA in year t and $R\&D_{it}^{histo}$ and IA_{it}^{histo} , the corresponding historical values.

Previous academic contributions have introduced more sophisticated measures of excess or investments, notably to test the empire building hypothesis (Baumol, 1959). For example, Frattaroli (2020) controls for firm age, sales, the presence of state ownership, ROA, book-to-market, and market leverage, in addition to industry and year fixed effects, to study the impact of the 2018 French Alstom Decree⁹ on

⁹ The 2018 French Alstom Decree designates energy, water supply, transportation, electronic communications and public health industries as strategic to the country's interest and enables the French public authorities to veto acquisition attempts of French firms active in these fields by foreign acquirers. Frattaroli (2020) shows that the adoption of this new legislation has significantly reduced the probability of being acquired for firms active in these industries.

investment (see Table 7 differences-in-differences specification). The variations control for the normal level of investments and allow one to isolate the effect of the treatment on the excess (or abnormal) investments. By doing so, Frattaroli (and similar approaches) focuses on the fraction of investments that can be considered as abnormal with respect to a reference model of normal investments. We do not adopt such a strategy because we are interested in the change of firm investment behavior through time in response to an increase in competition. Using the historical firm behavior as a reference allows us to isolate this change of behavior without any assumptions on a model of normal investment.

Table 2, Panel B, confirms that on the sample used to test the value decrease prediction, RICI is also close to 17%, with a highly right-skewed distribution. Excess R&D intensity is on average close to zero, as it should be if R&D intensity isn't trending during the analyzed time period in our sample, but is highly heterogeneous, with a standard deviation (3.5%) close to the average R&D intensity in the sample (4.2%). We also observe high heterogeneity for excess IA, with all three quartiles being equal to zero, while the standard deviation is huge with respect of the average (the untabulated coefficient of variation is 190).

Control Variables

To test the correlated investment prediction, we include in our multivariate specifications a set of time-varying firm level control variables, in addition to firm and year fixed-effects. Specifically, we control for firm size (the natural logarithm of total assets), profitability (ROA, defined as the ratio of operating income before depreciation to total assets), capital structure (leverage, defined as the ratio of long term debt and debt in current liabilities to total assets), liquidity (cash ratio, defined as the ratio of cash position to total assets), the nature of assets (intangible ratio, defined as the ratio of intangible assets to total assets) and valuation (MTB, the ratio of market value of equity to book value equity, with book equity computed as in Davis et al., 2000). Descriptive statistics are provided in Table 2. The average size of our firms is \$4,029 million (with a median of \$386 million (untabulated), highlighting the strong right skewness of the distribution of firm size), with a corresponding ROA of 6.9%, leverage of 20.9%, cash ratio of 13.1%, intangible ratio of 16.5% and MTB of 3.16. Compared to descriptive statistics reported for similar samples (Cheng et al. 2015), the numbers are on the order of magnitude of what we expect to find. For example, the authors report an average ROA of 10% and leverage of 22%. When testing the robustness of our results to endogeneity, we also use a measure of firm level R&D tax incentive as our instrumental variable, following Bloom and al. (2013), but we defer its description until Section 5.1.

Tests of the value decrease prediction rely on the Fama and French (1998) regression approach (Equation 1). The authors include a set of explanatory variables that include past, current, and future

values of dividends, interest, earnings, investment, and R&D expenditures, respectively denoted D_{it} , I_{it} , E_{it} , dA_{it} and RD_{it} . Additional notations are used for two year leads and lags: dX_{it} is the two year change in X_{it} ($dX_{it} = X_{it} - X_{it-2}$) and dX_{it}/A_{it} is the two year change in X_{it} scaled by total assets. We replicate these variables following the description in their Section 1. The inclusion of scaled two year leads and lags of dividends, interest, earnings, investment, and R&D expenditures aim to control for investor anticipations. The set of control variables is listed in Table 2, Panel B, with corresponding descriptive statistics. As the authors do not provide descriptive statistics, we are not in a position to compare to them. Note also that adding the control variables used to test the correlated investment prediction (firm size, ROA, leverage, liquidity, intangible ratio) does not alter our results (untabulated).

3.3. Econometric Specification

The Correlated Investment Prediction

The decisions to allocate resources to innovation internally, in the form of R&D expenses, and/or externally, to acquire innovative targets, are clearly interdependent. To account for this source of correlation, our baseline specification is a system of two simultaneous equations, one for R&D Intensity and the other for Innovative Acquisitions:

$$R\&D_{it} = \alpha_i + \beta_t + \gamma RICI_{it-1} + \delta IA_{it} + \mathbf{Controls}'_{it-1} \boldsymbol{\mu} + \epsilon_{it} \quad (6)$$

$$IA_{i,t} = \alpha_i + \beta_t + \gamma RICI_{it-1} + \delta R\&D_{i,t} + \mathbf{Controls}'_{it-1} \boldsymbol{\mu} + \eta_{it} \quad (7)$$

where $R\&D_{it}$ and $IA_{i,t}$ are our dependent variables, α_i are the firm fixed-effects, β_t are the year fixed-effects, $RICI_{i,t-1}$ is the lagged value of our independent variable, $\mathbf{Controls}'_{i,t-1}$ is the lagged values of our vector of control variables (we use bold notation for vectors), $\epsilon_{i,t}$ and $\eta_{i,t}$ are the errors terms. Under the correlated investment prediction of the Arms Race hypothesis, we expect that γ is positive in Equations 6 and 7.

Keeping in mind that the variable of interest is RIC, the presence of IA at the right-hand side of Equation 6 and R&D at the right-hand side of Equation 7 allows us to control for one source of endogenous omitted variable bias due to the omission of these variables thanks to the Conditional Mean Independence Theorem (Stock and Watson, 2020, Section 6.8)¹⁰. We defer the treatment of potential endogeneity of

¹⁰ Coefficients of the IA and R&D can however not be given any causal interpretation as the rank and order conditions for identification are not met.

RICI itself, our independent variable for which a causal interpretation is relevant, to the robustness check Section 5.1. We also report results without R&D and IA as right-hand side variables to check whether our results are affected by the bad controls issue (Angrist and Pischke, 2009).

The Value Decrease Prediction

The test of the Arms Race hypothesis' value decrease prediction relies on expanded versions of the Fama and French (1998) regression specification:

$$\ln MTBA_{it} = \alpha_i + \beta_t + \gamma RICI_{it} + \delta R\&D_{it} + \tau (RICI_{it} \times R\&D_{it}^{excess}) + \theta (RICI_{it} \times R\&D_{it}^{histo}) + \mu IA_{it} + \mathbf{Controls}'_{it} \mathbf{v} + \epsilon_{it} \quad (8)$$

$$\ln MTBA_{it} = \alpha_i + \beta_t + \gamma RICI_{it} + \delta IA_{it} + \tau (RICI_{it} \times IA_{it}^{excess}) + \theta (RICI_{it} \times IA_{it}^{histo}) + \mu R\&D_{it} + \mathbf{Controls}'_{it} \mathbf{v} + \eta_{it} \quad (9)$$

where **Controls** is the vector of Fama and French (1998) explanatory variables, namely E_{it}/A_{it} , dE_{it}/A_{it} , dE_{it+2}/A_{it} , dA_{it}/A_{it} , dA_{it+2}/A_{it} , RD_{it}/A_{it} , dRD_{it}/A_{it} , dRD_{it+2}/A_{it} , I_{it}/A_{it} , dI_{it}/A_{it} , dI_{it+2}/A_{it} , D_{it}/A_{it} , dD_{it}/A_{it} , dD_{it+2}/A_{it} and dV_{it+2}/A_{it} . We intentionally use contemporaneous dependent and independent variables because we expect to the value implications of public information of firm innovation investments to be incorporated in the contemporaneous year. Under the value decrease prediction and assuming that investors do not (fully) anticipate the start of an innovation arms race process, we expect τ to be negative in Equation 8 and in Equation 9. These equations are estimated by ordinary least squares and standard errors are clustered at the firm-year level, to account for the panel structure of our dataset (Petersen, 2009).¹¹ We report a test of investors' anticipations around rival innovative acquisition announcement in Appendix 2. Results are consistent with our assumption of no (or limited) arms race anticipations.

¹¹ One may worry that the simultaneous presence of the MTB ratio as a control variable in investment Equations 6 and 7 and the contemporaneous $\ln MTBA$ as dependent variables in value Equations 8 and 9 generates some form of circularity or one more bad control issue (Angrist and Pischke, 2009). In our view, this is unlikely because the investment and value equations are separate specifications and, moreover, the MTB ratio is lagged by one year in the investment equations. Notwithstanding, we replicate our results excluding the MTB ratio from the investment equation and obtain similar results (untabulated).

As emphasized in Figure 1, it is the combination of positive γ in Equations 6 and 7 (correlated investment) and negative τ in Equations 8 and 9 that discriminate the Arms Race hypothesis from the Schumpeter (1943) Rent Dissipation and the Arrow (1962) Competition Escape hypotheses.

4. Results

4.1. The Arms Race Hypothesis – Grand Average Results

We start by reporting average results obtained for the whole cohort of firms and over the whole 1996 to 2019 period. Table 3 reports six specifications: the first four report results for the correlation investment prediction and the last two, for the value decrease prediction. Columns 1 and 2 contain estimates of Equations 6 and 7 respectively (that rely on conditional mean independence to control for simultaneity of decisions between R&D investments and innovative target acquisitions) and Columns 3 and 4, estimates of Equations 6 and 7 excluding R&D and IA as right-hand side variables (to check the robustness of our results to the potential bad control issues). Columns 5 and 6 present estimates of Equations 8 and 9.

The results show a clear picture: in Columns 1 to 4, the coefficient of RICI is positive and highly significant, consistent with the correlated investment prediction: lagged innovative acquisitions by rivals drives firms to invest more in R&D and IA. Moreover, these effects are economically sizable: a one standard deviation increase in RICI increases R&D by 4.31 % and IA by 49.16 % with respect to their unconditional averages. Notably, the RICI coefficient estimates are almost unchanged between Columns 1 and 2 and Columns 3 and 4: the interdependence between R&D and innovative acquisitions does not affect firm reactions to rival moves, as measured by RICI, and our results are not biased by a bad control issue. In Column 5, the coefficient of the interaction term between RICI and excess R&D is negative and significant at the 5% confidence level, while in Column 6, the coefficient of the interaction term between RICI and excess IA is negative at the 1% confidence level, in support of the value decrease prediction. The economic effects are smaller than for the correlated investment prediction but yet sizeable: a one standard deviation increase in rivals' IA (count based) combined with a one standard deviation increase in firm excess R&D leads to a lnMTBA decline of 2.5%. A similar result is observed in the case of one standard deviation increase in firm excess IA. The combination of Columns 1 to 4 results (correlated investment prediction test) and Columns 5 to 6 results (value decrease test) bring strong support to the Arms Race Hypothesis: M&A transactions focused on innovative targets trigger more resource allocation to innovation by acquirer rivals, not less, and these investments in innovation negatively affect the firm's

value. One policy implication of the finding that these acquisitions spur innovation is that the M&A market contributes to foster economic growth through this channel as long as we accept that innovation contributes to growth.

We report estimates with the full set of control variables in Appendix I.A.1 Table 3. Some control variables display noteworthy coefficient estimates, even if we must refrain from any causal interpretation. In Column 1, firm size is negatively correlated with R&D investment, like ROA and leverage. As we control for firm fixed-effects, these estimates indicate that increase in size, profitability, and leverage are correlated with less R&D spending at the firm level. Similar conclusions hold for innovative acquisition's correlation with leverage and asset tangibility (Column 2). On the contrary, an increase in growth opportunities and/or firm valuation (MTB) is positively correlated with innovative acquisition undertakings. This last result is at first sight consistent with the positive correlation reported in the literature between lagged firm valuation and future M&A activity (e.g., Rhodes-Kropf et al., 2005), but the negative relation between firm value and a specific type of acquisition (contemporaneous excess innovation acquisitions under the pressure of rivals in Column 6) highlights that interactions between these variables are probably more complex. Point estimates of Fama and French (1998) explanatory variable coefficients are significantly different from estimates reported by the authors (see authors' Table 2), as to be expected taking account of the difference in estimation strategy (Fama and French (1998) use a Fama-MacBeth regression approach while our results rest on a fixed-effects panel data estimator) and analyzed periods (Fama and French (1998) study the 1965 to 1992 period). Notwithstanding, restricting our attention to statistically significant coefficients, thirteen out of the fourteen variables display a similar sign, the only exception being the coefficient of dI_{it}/A_{it} , a result highlighting the robustness of the Fama and French (1998) study.

We next focus on three alternative M&A and firm samples: change of control transactions (we restrict our M&A sample to cases where the acquirer holds less than 50% before the transaction and more than 50% after, a subsample of 39,863 transactions), acquisitions of public targets (a subsample of 7,273 transactions) and horizontal M&A transactions (the acquirer and the target share the same 3-digit SIC code, a subsample of 22,931 transactions). Results are reported in Table 4 and are obtained with the inclusion of R&D and IA as right-hand side variables to control for simultaneity between R&D and innovative acquisition decisions, like in Table 3 Columns 1 and 2. Table 4 structure is otherwise similar to Table 3 to ease comparison of results. The main take-aways from Table 4 can be summarized as follows:

- Change of control transactions (Table 4, Panel A): in Columns 1 and 2 (the correlated investment prediction test), coefficient estimates of lagged RICI remain positive and highly significant in both the R&D and the IA equations. In both cases, the point estimates are similar to point estimates reported in Table 3. In Columns 3 and 4 (the value decrease prediction test), coefficient estimates of the interaction terms between RICI and excess R&D and RICI and excess IA are negative, and significant at the 5% confidence level in Column 3 and 1% confidence level in Column 4, with coefficient point estimates that are again close to the ones reported in Table 3. Restricting our sample to change of control transactions does not significantly alter our results;
- Acquisitions of public targets (Table 4, Panel B): two coefficients of interest lose their significance (in Column 1, in the *R&D* equation, the coefficient on lagged RICI and in Column 4, the coefficient of the interaction term between RICI and excess IA). Point estimates are significantly smaller than in Table 3, except in Column 3. The Arms Race Hypothesis predictions find weaker support using this sub-sample restricted to public targets. This is consistent with private firms playing an important role in innovation in the economy (Gao et al., 2018) but also with a loss of statistical power of our tests due to a drastic M&A sample restriction (from 9,336 transactions to 1,322);
- Horizontal transactions (Table 4, Panel C): finally, restricting our M&A sample to horizontal transactions also does not affect our results, except that in Column 4, the coefficient of the interaction term between RICI and excess IA loses its statistical significance (but keeps its negative sign). Like for control transactions, results are consistent with the Arms Race Hypothesis predictions, with coefficient points estimates on the order of magnitude of estimates reported in Table 3 (except again in Column 4). This is a noteworthy result because it has policy implications: the positive effect of rivals' innovative acquisitions on the firm incentives to invest in innovation is confirmed for transactions specifically subject to stricter regulation but we can not exclude that this is a manifestation of the regulation deterrence effect.

4.2. The Arms Race Hypothesis – Sector Level Results

Average results mask potentially significant industry heterogeneity, even if our inclusion of firm fixed-effects should absorb a large part of it¹². As such, we conduct sector level analyses next. These investigations at the sector level must balance granularity against statistical power: the finer grained the chosen classification, the more homogenous are the firm characteristics, a desirable property to

¹² Firm level SIC code updates are infrequent updated and therefore, SIC industry dummies are mostly time-constant variables

investigate innovation incentives. But the finer grained the classification, the lower the statistical power of our regressions because the number of firm-year observations is drastically reduced. This is particularly problematic because our goal is to identify whether the Arms Race Hypothesis process is at work. A low power test would lead us to erroneously fail to reject the null hypothesis of no effect of rivals IA on incentives to innovate and firm value (a type II error) for many industries, failing to detect the potential presence of negative effects. We decide therefore to favor statistical power and to adopt the Fama and French five industries classification¹³: Fama and French provide a matching table that allows us to group SIC codes into Consumer, Manufacturing, High-Technology, Healthcare, and Others. We use historical SIC codes collection in the CRSP database to place firm-year observations into the corresponding sectors.

Table 5 reports our results. Each panel is organized as in Table 3 to ease comparison, except that Table 3 Columns 3 and 4 are dropped because our results are clearly unaffected by the issue of the bad control (see Section 4.1). Panel A focuses on the Consumer sector (11,974 and 7,385 firm-year observations, respectively for the correlated investment prediction test and the value decrease prediction test), where we see that the Arms Race Hypothesis predictions find no support. We reach a similar conclusion for the Manufacturing sector (with sub-samples of 14,585 and 9,350 firm-year observations). In contrast, results for the High-Technology sector (Panel C) bring support to both the correlated investment and the value decrease predictions (except in Column 3, where the coefficient of the RICI times excess R&D interaction terms is negative but not statistically significant). Notably, point estimates of RICI coefficients (0.010 and 0.148 in Columns 1 and 2) are higher than the corresponding point estimates reported in Table 3 for the whole sample of firms (0.008 and 0.122 respectively: the effect of an increase in rivals IA on innovation investments is stronger in the High-Technology sector. These results are obtained with sub-samples of 16,586 and 9,362 firm-year observations). Panel D (Healthcare) results show support for the Arms Race Hypothesis with respect to R&D responses, but not for innovative acquisitions: the coefficient of RCI in Column 1 (the R&D part of the correlated investment prediction) is positive (with a point estimate higher than the one reported in Table 3) and statistically significant at the 5% confidence level and the coefficient of the interaction term between RICI and excess R&D is negative in Column, in support with the value decrease prediction, but statistically significant only at the 10% confidence level. Rivals' IA appear to have however no significant effect on the firm IA (Column 2) and value (Column 4). Sub-samples of firm-year observations are here smaller (5,950 and 3,497 respectively). As expected for the Others sector, which is

¹³ Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

a catch all for unrelated firms not grouped into the other 4 sectors, coefficients not significant (except in Column 2), most probably because rivals are poorly identified here.

While we cannot exclude the possibility that part of these conclusions are due to a lack of power to reject the null hypothesis of no effect (sample sizes are drastically reduced as emphasized above), the dependence of our results to the sector is intuitive: innovation is certainly a powerful driver of competition in the High-Technology and, to some extent, in the Health-Care sectors and therefore, these offer conditions favorable to the emergence of arms races between competitors.

4.3. The Arms Race Hypothesis – Within-Industry Results

The dependence of firms' response to competitive shocks to its within industry situation is rooted in Schumpeter (1943) and Arrow (1962). Schumpeter argues that competition erodes producer rents. Under this Rent Dissipation Hypothesis, an increase in competition puts producers under financial pressure, erodes anticipated future innovation rents and leads them to cost-cutting strategies, including cutting innovation investments. This should be especially the case for weaker industry participants (industry laggards henceforth), as these are already constrained before the increase in competition. On the other hand, Arrow argues that in response to an increase in competition, firms will invest more in innovation to restore their quasi-monopoly rents (the Competition Escape Hypothesis). Strong industry participants (industry leaders henceforth) are in the best position to follow this strategy because they have sufficient financial resources. The Schumpeterian rent-dissipation and Arrow escape-competition hypotheses provide mechanisms explaining the dependence between industry participants' competitive position and their willingness to invest in innovation in reaction to competitive shocks. More recently, Aghion et al. (2005) argue that the relation between innovation and competition follows an inverted-U relation. So called neck-and-neck firms (firms in fierce competition with rivals) are the most willing to invest in innovation because returns of these investments are the greater for them. In this section, we explore the relation between firm R&D and IA investments, their valuation consequences, rivals' IA (the competitive shock), and firm within-industry position.

We start with the Schumpeterian rent-dissipation and Arrow escape-competition hypotheses. Our first step is to identify industry leaders and laggards. We build an empirical proxy based on profitability (ROA) and market shares (sales based)¹⁴. For each year and each 3-digit SIC industry, we sort firms by ROA and market shares. Industry leaders are firms that are in the highest quartile of ROA and in the highest

¹⁴ We test several alternative definitions of leaders and laggards based on quartiles in place of medians criteria and addition cash ratio based criteria. Results appear to be highly robust to these variations (untabulated).

quartile of market shares (the most profitable and largest industry players). Industry laggards are symmetrically obtained: they are firms in the lowest quartile of ROA and in the lowest quartile of market shares (the least profitable and smallest industry players).

We next augment Equations 6 and 7 with interaction terms to test whether firms' within-industry positions affect the relation between subject firm R&D and IA and rivals' IA (the correlated investment prediction) :

$$R\&D_{it} = \alpha_i + \beta_t + \gamma_0 (Leaders_{it} \times RIC_{it-1}) + \gamma_1 (Laggards_{it} \times RIC_{it-1}) + \gamma_2 (Others_{it} \times RIC_{it-1}) + \delta IA_{it} + \mathbf{Controls}'_{it-1} \boldsymbol{\omega} + \epsilon_{it} \quad (10)$$

$$IA_{it} = \alpha_i + \beta_t + \gamma_0 (Leaders_{it} \times RIC_{it-1}) + \gamma_1 (Laggards_{it} \times RIC_{it-1}) + \gamma_2 (Others_{it} \times RIC_{it-1}) + \delta R\&D_{it} + \mathbf{Controls}'_{it-1} \boldsymbol{\omega} + \eta_{it} \quad (11)$$

where $Leaders_{it}$ is a dummy variable equal to one if the firm i is an industry leader in year t , $Laggards_{it}$ is a dummy variable equal to one if it is an industry laggard, $Others_{it}$ is a dummy variable equal to one otherwise¹⁵. Other notations are as in Equations 6 and 7. We are particularly interested in coefficients γ_0 and γ_1 , that capture interactions between within-industry position and competition shocks due to rivals' IA.

We similarly augment Equations 8 and 9 with interactions terms to test whether firms' within-industry positions affect the relation between firm value and the interaction between rivals' IA and firm excess R&D and firm excess IA (the value decrease prediction)¹⁶.

Table 6, Panel A reports our results, again organized as Table 3 to ease comparison. In addition to the standard set of statistics, we report heteroskedastic robust Fisher tests of coefficient equality between $Leaders_{it} \times RIC_{it-1}$ and $Laggards_{it} \times RIC_{it-1}$ interaction terms (Columns 1 and 2) and $Leaders_{it} \times RIC_{it} \times R\&D_{it}^{excess}$ and $Laggards_{it} \times RIC_{it} \times R\&D_{it}^{excess}$ interaction terms (Columns 3 and 4) at the bottom of the table. Both industry leaders and industry laggards invest significantly in R&D under the pressure of rivals' IA (correlated investment prediction) but, while laggards invest more in R&D (Column 1), this is to say in organic innovation, leaders invest more in IA (Column 2), this is to say to buy

¹⁵ Note that we do not include the variable RIC_{it-1} because it would be perfectly colinear with the combinations of $(Leaders_{it} \times RIC_{it-1})$, $(Laggards_{it} \times RIC_{it-1})$ and $(Others_{it} \times RIC_{it-1})$. Equations 10 and 11 regression specifications allows us the decompose the effect of RIC_{it-1} on the dependent variable between industry leaders, laggards and other firms.

¹⁶ The interaction terms $(RIC_{it} \times R\&D_{it}^{excess})$ and $(RIC_{it} \times IA_{it}^{excess})$ are excluded to avoid again perfect multicollinearity.

innovation externally. Moreover, in reaction to an increase of rivals' competitive pressure, leaders are more willing (or more able) to pursue IA than the average firm in the industry (untabulated). Concerning the value effects of these investments (the value decrease prediction), we observe negative and significant coefficients of industry leaders for excess R&D (Column 3) and excess IA (Column 4). Moreover, the difference between leaders and laggards is statistically significant for excess R&D, as indicated by the Fisher test reported in Column 3. The Arms Race Hypothesis predictions get stronger support for industry leaders than industry laggards, especially on the IA side.

We next turn to the Aghion et al. (2005) inverted-U relationship. We follow Chen and Wu (2019) and use HP similarity scores to create our neck-and-neck competition indicator variable, denoted $Neck\&Neck_{it}$, and its complement, denoted $Others_{it}$. For each year and each firm, we collect the ten closest rivals in the product market space and compute their third quartile similarity score. Firms in neck-and-neck competitions are the ones above the median of the yearly distribution of these third quartile similarity scores. Next, we replace interaction terms with $Leaders_{it}$, $Laggards_{it}$ and $Others_{it}$ dummy variables by interaction terms with $Neck\&Neck_{it}$ and $Others_{it}$ dummy variables.

Results are reported in Panel B of Table 6. The correlated investment prediction is confirmed for neck-and-neck firms: under the pressure of rivals' IA, these firms increase R&D and IA more than firms not that much under pressure of competition (correlated investment prediction, Columns 1 (significant difference) and 2 (difference is only close to statistical significance at usual levels). These increases in innovation investments negatively impact the firm valuation (value decrease prediction, Columns 3 and 4), and more so for neck-and-neck firms in case IA (Column 4).

These results show that within-industry competitive position affects firm level reactions to an increase in competitive pressure due to rivals' innovative acquisitions. Notably, our results remain compatible with the grand average reported in Table 3: whether for industry leaders and laggards (Panel A) or for industry neck-and-neck firms (Panel B), all coefficients of interaction terms with RICl are positive in Columns 1 and 2, consistent with the correlated investment prediction, and all coefficients of interaction terms with RICl times excess R&D and RICl times excess IA are negative for the value equations, consistent with the value decrease prediction.

5. Additional investigations and Robustness checks

5.1. Rivals Innovative Acquisition Endogeneity

While it seems improbable that our test of the correlated investment prediction (Equations 6 and 7) are exposed to some simultaneity or reverse causality sources of bias (we lag our independent variable RICl by one year and therefore, future firm innovation investment decisions would have to drive past rivals innovative acquisitions), potential endogenous omitted variables remain a concern. The issue is of importance because giving a causal interpretation to our results supporting the correlated investment prediction has policy implications: if rivals' IA drive firm investments in R&D and IA higher, policymakers should not be concerned about aggregate adverse side-effects of these M&A transactions on innovation.

We control for time invariant latent factors with firm fixed-effects, time-varying latent factors common to all firms with year fixed-effects and a set of firm-level time-varying characteristics (profitability, capital structure, liquidity, nature of assets, and valuation). Nonetheless, one may argue that some additional time-varying latent factors correlated to both past rivals' innovative acquisitions and a firm's decision to invest in R&D and to acquire innovative targets are at play. Therefore, we decide to test the validity of the causal interpretation of our results using an instrumental variable approach.

We select state-wide R&D tax credits as an instrument for rivals' innovative acquisitions. The U.S. federal R&D tax credit was introduced in 1981 and progressively implemented in U.S. states afterwards. This staggered adoption led 32 U.S. states to provide R&D tax credits by 2006. Hombert and Matray (2018) emphasize that these state R&D policies generate significant exogenous decreases in the user cost of R&D across states and time. Therefore, firms benefit from these incentives to invest in R&D depending on the location of their R&D activities. We use the Hall-Jorgenson user cost of R&D as an instrument, replicating the procedure described in Bloom et al. (2013) Internet Appendix B.3.1. Valid instruments must satisfy the relevance, exclusion, and independence assumptions. We argue that these are satisfied with the tax credits:

- Relevance: R&D tax credits increase firm incentives to invest in R&D and, to the extent to which firms face funding constraints, we expect that increased incentives to invest in R&D should lower incentives to acquire innovative targets. This is a testable assumption;
- Exclusion: The instrument works through another state's tax change that affects rivals located in that state, but not the subject firm located in a different state. As such, these out-of-state tax-credit changes should not directly affect the firm's own decisions to invest in innovation (whether organically through R&D or externally through innovative acquisitions). The correlation between the firm innovation investment decisions and the rivals' R&D incentives takes place through the change in competitive pressure that the rivals' behavior generates. As is typical, this exclusion restriction is not testable per se but it appears to us reasonable in the present case;

- Independence: Bloom et al. (2013) suggest that the introduction and level of U.S. tax credits were largely unrelated to the economic environment into which firms operate and Hombert and Matray (2018) provide additional results consistent with this claim.

Because our independent variable of interest is computed for the firm 10NN rivals portfolio, we collect the Hall-Jorgenson user cost of R&D for these same firm rivals, use them to predict rival firm level investment in R&D due to tax credits incentives and finally, take the average of these predicted values (denoted $R\&DUC_{i,t}^{10NN}$) to obtain our instrument for $RICI_{i,t}$. We anticipate that the average 10NN user cost of R&D will be negatively correlated with $RICI_{i,t}$ because, as explained above, increased incentives to invest in R&D should lower incentives (at least relatively speaking) to acquire innovation externally.

We obtain our instrumental variable estimates using 2SLS. In the first stage, we regress $RICI_{i,t}$ on $R\&DUC_{i,t}^{10NN}$ and all other control variables:

$$RICI_{i,t} = \alpha_i + \beta_t + \gamma R\&DUC_{i,t}^{10NN} + \delta IA_{it} + \mathbf{Controls}'_{i,t-1} \boldsymbol{\mu} + \epsilon_{i,t} \quad (12)$$

or

$$RICI_{i,t} = \alpha_i + \beta_t + \gamma R\&DUC_{i,t}^{10NN} + \delta R\&D_{i,t} + \mathbf{Controls}'_{i,t-1} \boldsymbol{\mu} + \epsilon_{i,t} \quad (13)$$

We next regress $R\&D_{i,t}$ and $IA_{i,t}$ and the lagged fitted values of $RICI_{i,t}$ (denoted $RICI_{i,t-1}^{fit,1}$ using Equation 12 and $RICI_{i,t-1}^{fit,2}$ using Equation 13) and the firm own user cost of R&D (denoted $R\&DUC_{i,t}$):

$$R\&D_{i,t} = \alpha_i + \beta_t + \gamma RICI_{i,t-1}^{fit,1} + \delta R\&DUC_{i,t} + \mu IA_{it} + \mathbf{Controls}'_{i,t-1} \boldsymbol{\nu} + \epsilon_{i,t} \quad (14)$$

$$IA_{i,t} = \alpha_i + \beta_t + \gamma RICI_{i,t-1}^{fit,2} + \delta R\&DUC_{i,t} + \mu R\&D_{i,t} + \mathbf{Controls}'_{i,t-1} \boldsymbol{\nu} + \eta_{i,t} \quad (15)$$

We use the standard two-stage least square estimator, standard errors are clustered at the firm level and adjusted to take into account the two-stage nature of this procedure. The presence of $R\&DUC_{i,t}$ as a right-hand side variable in Equations 14 and 15 is particularly important because $R\&DUC_{i,t}$ and $R\&DUC_{i,t}^{10NN}$ are potentially correlated and we have therefore to partial out the firm own R&D user cost incentives to invest in R&D to obtain an unbiased estimate of γ , the coefficient of interest. We limit the period under investigation to 1996-2010 because the latest U.S. states to adopt R&D tax credits in the Wilson (2009) dataset did so in 2006, keeping that way a 5 years post treatment period.

Results are displayed in Table 7. Columns 1 and 2 are dedicated to the R&D part of the correlated investment prediction (corresponding to Column 1 in Table 3), reporting the first stage and second stage estimation results respectively and Columns 3 and 4 to the IA part of the correlated investment prediction (corresponding to Column 2 in Table 3), reporting likewise first and second stages estimation results respectively. Let us first comment on the first stage estimates. As anticipated, the coefficient of $R\&DUC^{10NN}$ is negative and highly statistically significant in Columns 1 and 3 (the Fisher statistic is close to 40): increased incentives to invest in R&D reduce rivals' innovative acquisition intensity. The coefficient on lagged instrumented RICl is positive and statistically significant both in the R&D equation (Column 2) and the innovative acquisition equation (Column 4). One may worry about the point estimates (respectively 0.089 and 1.348), that could appear very high with respect to point estimates reported in Table 3 (respectively 0.008 and 0.122). Jiang (2017) points out indeed that this can signal a first stage weak instrument issue but our first stage test of significance indicates that this is not the case. However, as clarified in Angrist and Pischke (2009), the Local Average Treatment Effect theorem tells us that the instrumental variable estimate is valid only for compliers (the subsample of rival firms that decrease their innovative acquisitions due to R&D tax credits, in our case). This subsample of firms is potentially significantly different from firms that do not change their acquisition strategies regardless of the tax credits they are offered (e.g.: firms that do not undertake any acquisition, or "never-takers" in Angrist and Pischke terminology). These instrumental variable-based results confirm therefore that the positive relation between rivals' IA and firm R&D and innovative acquisitions is not an artifact due to the action of some latent factors, but one must remain aware that they do not provide an estimate of the magnitude of the causal relation for the whole cohort of firms that we track.

5.2. Innovation Investments Efficiency

Our results are consistent with the value decrease prediction of the Arms Race Hypothesis: a negative relation between the firm market value and the interaction between the rivals' IA (RICl) and excess investments in innovation (R&D and IA) can be driven by a sub-optimal investment policy, generating a decline in innovation investment efficiency, or by a transfer of economic rents beneficial to consumers. We explore in this section whether a decline in innovation investment efficiency is observable using information collected in the NBER Patent Citation Data file Hall et al., 2001. Our measures of innovation outputs are the logarithm of the three years forward cumulated number of patents or citations. Due to data availability constraint (the NBER data are available only up to 2006) and the three-year window over which patents and patents citations are cumulated, our analyzed period ends in 2003. Our results are

therefore obtained for a limited subsample of 4,147 observations and, from that perspective, remain exploratory. The estimated econometric specification parallels the one used to test the value decrease prediction of the Arms Race Hypothesis (Equations 8 and 9), substituting our measures of innovation output for the InMBTA dependent variables and our standard set of control variables (ROA, leverage, cash, intangibility and equity MTB ratios) for the Fama and French (1998) explanatory variables.

Results are reported in Table 8, Panel A for patents and Panel B for patents citations. In each case, Column 1 focuses on excess R&D and Column 2 on excess IA, like in Table 3. A clear message emerges from these estimates: no decline in innovation investment efficiency is observable. The only coefficient of interest that is statistically significant appears in Column 2 of Panel B (the coefficient of RICI and excess IA interaction term), but it is positive. Absent a decline in investment efficiency, the observable decline in firm market value in the wake of excess innovation investments under pressure of rivals is consistent with a transfer of rents beneficial to consumers. Such a tentative conclusion, if confirmed on larger datasets, would be one more reason for regulatory authorities to be less concerned about the M&A side-effects on innovation incentives on average.

We also use the Kogan et al. (2017) dataset that covers our entire sample period to replicate the above reported NBER Patent Citation Data file-based analyses and obtain similar results (untabulated).

5.3. Analyses on the Extensive Margin

As mentioned in the introduction, up to now our analyses are performed on the intensive margin, keeping only firms whose rivals did perform acquisitions, to avoid producing results driven by firms never exposed to such rivals' moves. But one might be concerned that our inferences are muddled by focusing only on firms that are exposed to rival pressure. For example, it could be that firms with no rival pressure are also taking the same innovation actions, a finding that would increase the case for an omitted driver. In this section, therefore, we replicate our baseline analyses (Table 3) on the extensive margin, that is keeping all firms, whether or not their 10*NN* rivals undertook some acquisitions. This leads to the addition of roughly 20,000 firm-year observations to our sample.

Table 9 reports the results. The two predictions of the Arms Race Hypothesis are again strongly supported. Moreover, the coefficient point estimates are close to the ones reported in Table 3 (analyses on the intensive margin). If it were the case that firms with no rival pressure were taking similar actions, the point estimates on the pressure variables would have decreased, perhaps to zero. Thus, our results are not a byproduct of the exclusion of firms never exposed to rivals' IA from our sample.

5.4. Value Based Analysis

Our measure of rivals' IA, RICl, is count-based (see Equation 1). A corresponding value-based measure of rivals' IA can easily be constructed by simply weighting each acquisition by its deal value as reported in the SDC database. Two potential shortcomings of such approach are that the M&A transactions for which the SDC database doesn't report the deal value will be excluded from the analysis and, taking into account the extreme right skewness of the M&A deal value distribution, a limited number of large transactions may drive the generated results. Notwithstanding these issues, we replicate our results using this value-based measure of rivals IA (denoted RIVI) and report the results in Internet Appendices 2 to 8.

To summarize, the results are mostly unchanged. This is the case for baseline results (Table IA.2 and for analyses by subsamples (Table I.A.3), except that the excess R&D value decrease prediction loses support. Analyses by industry (Table I.A.4) confirm that the High-Technology Industry is driving the results. Within industry analyses (Table I.A.5) confirm the role of industry leaders. Instrumental variable based results (Table I.A.6) are again statistically significant, both at the first stage (rejecting the null hypothesis of weak instrument) and at the second stage, confirming the causal interpretation of the relation between rivals' IA and the intensity of firm investments in innovation (the correlated investment prediction). Finally, innovation investment efficiency shows no sign of decline (Table I.A.7) and results obtained on the extensive margin are consistent with results obtained on the intensive margin (Table I.A.8).

5.5. Additional Robustness Checks

Fighting the omitted variable bias is a permanent endeavor in empirical corporate finance research. Our econometric specifications rely on the use of panel data with firm fixed effects that absorb time-constant firm level unobservables and time-varying control variables as a first solution. Time-varying latent factors could still affect our results. For example, one may argue that factors such industry concentration, market power, growth opportunities or technology shocks will impact firm decisions to invest in innovation and their valuation, and are correlated with rivals' behaviors. To investigate whether our results are biased by such source of omitted variables, we augment our baseline specifications with 3-digit SIC industry times year fixed effects that will absorb all such factors. As an illustration, Equation 6 becomes:

$$R\&D_{it} = \alpha_i + \beta_t + (SIC3_{it} \times \beta_t) + \gamma RICl_{it-1} + \delta IA_{it} + \mathbf{Controls}'_{it-1} \boldsymbol{\mu} + \epsilon_{it} \quad (16)$$

where $SIC3_{it}$ are 3-digit SIC industry fixed effects and β_t are year fixed effects. Results are reported in Table I.A.10. Panel A that replicates Table 3 count-based analysis Columns 1 and 2 for the correlated investment prediction and Columns 5 and 6 for the value decrease predictions. Panel B is dedicated to value-based analyses, as reporting in Table I.A.2. Our results are qualitatively comparable.

Our measure of intensity of innovative acquisitions by rivals, denoted RICl, uses the count of rivals' acquisitions as its denominator (see Equation 1). It is therefore legitimate to question whether our results are not driven by the intensity of rival acquisition activities more than by innovative acquisitions themselves (a denominator effect). We investigate this issue by using the aggregate values of rivals' total assets as an alternative scaling factor. This leads us to define a new measure of intensity of rival innovation acquisitions as:

$$RIAT_{it} = \frac{RIAV_{it}}{AggRAT_{it}} \quad (17)$$

where we use the same notations as in Equation 1 and $AggRAT_{it}$ is the sum of firm i product market space ten nearest neighbors rivals' total assets in year t . Note that the numerator, $RIAV_{it}$, is this time the aggregate value of rivals' innovative acquisitions (in place of the count as in Equation 1) to keep consistency between the numerator and denominator measurement units. Results are reported in Table I.A.11., where Columns 1 and 2 replicates Table 3 Columns 1 and 2 (tests of the correlated investment prediction) and Columns 3 and 4 replicates Table 3 Columns 5 and 6 (tests of the value decrease prediction). Our results are again qualitatively unchanged.

Koh et al. (2021) assess the reliability of various methods for dealing with unreported innovation activities (in particular R&D expenses and patents). Extensive analyses lead the authors to recommend the use of multiple imputation to handle this issue. Our test of the correlated investment prediction uses R&D expenses collected in Compustat scaled by total assets as the dependent variable (see Equation 6) and is therefore the econometric specification that we estimate that is most exposed to this source of bias. We follow Koh et al. (2021) recommendations and replicate Equation 6's estimation using a regression based multiple imputation approach. All firm-level control variables included in Equation 6 (ROA, leverage, cash, intangibility and MTB) are used in the regression specification imputing R&D missing values. Results are obtained with 50 replications, using the Gaussian normal regression imputation method. Table I.A.12 Column 1 displays the coefficient of RICl, our measure of rivals' innovation

acquisition intensity, to be compared to Table 3 Column 1's result, and Column 2 to the value based corresponding result, to be compared with Table I.A.2 Column 1. Obtained estimates are similar to results obtained replacing R&D expenses by zero when missing, as we do in our baseline specification.

6. Conclusion

The Arms Race Hypothesis predicts that investment in innovation increases under the pressure of rivals (the correlated investment prediction), generating a decline in firm valuation due to duplicative efforts that result in increased investment that simply maintains the status quo competitive positions (the value decrease prediction). Tracking a large cohort of firms over the 1996 to 2017 periods and using the Hoberg and Phillips (2010) similarity scores to identify firm rivals in the product market space, our results strongly support these predictions. Additional analyses emphasize the importance of taking into account M&A transactions targeting private firms to study these incentives mechanisms, the driving role of the High-Technology Industry (and, to a lesser extent, Healthcare) and the within-industry heterogeneity of behaviors, depending on the competitive position of firms (industry leaders appear to be more prone to engage in an innovation arms race). Moreover, our results warrant a causal interpretation of the relation between rivals' innovative acquisitions and the firm innovative investment response and hold whether we work at the intensive or extensive margin.

These results have significant policy implications: while each case is different, in general, regulatory authorities should less aggressively intervene in the M&A market out of concern for negative side-effects on innovation incentives. M&As appear, on average, to foster the innovation arms' race, driving the Baumol (2002) innovation engine.

Some of the analyses performed in this work remain exploratory and open the door to interesting future research. In particular, within-industry heterogeneity of firm response to rival pressures certainly deserves additional work, including refining our leaders, laggards and neck-and-neck classifications. Also, effects on innovation investment efficiency are at best tentative at this stage and should be backed by results obtained on a larger cohort of firms and longer period of time.

References

- Aghion, Ph., Howitt, P., 1992, A model of growth through creative destruction, *Econometrica*, 60, 323-51
- Aghion, Ph., Bloom, N., Blundell, R., Griffith, R., Howitt, P., 2005, Competition and innovation: An inverted-U relationship, *Quarterly Journal of Economics*, 120, 701–728
- Aktas, N., de Bodt, E., Roll, R., 2013, MicroHoo: Deal failure, industry rivalry, and sources of overbidding, *Journal of Corporate Finance*, 19, 20-35
- Alexandridis, G., Antypas, N., Travlos, N., 2017, Value creation from M&As: New evidence, *Journal of Corporate Finance*, 45, 632-650
- Angrist, J. D., Pischke, J.S., 2009, *Mostly Harmless Econometrics*, Princeton University Press
- Arrow, Kenneth, 1962, Economic welfare and the allocation of resources for invention, in R. Nelson, ed., *The rate and direction of inventive activity: Economic and social factors* (Princeton, NJ: Princeton University Press)
- Atanassov, J. ,2013, Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting, *Journal of Finance*, 68(3),1097–13
- Baumol, W., 1959, *Business Behavior, Value and Growth*, Macmillan, New-York
- Baumol, W., 2002, *The Free-Market Innovation Machine*, Princeton University Press, New Jersey
- Bellstam, G., Bhagat, S., Cookson, J. A., 2017, Innovation in Mature Firms: A Text-Based Analysis, Working Paper, Available at SSRN: <https://ssrn.com/abstract=2803232>
- Bena, J., Li, K., 2014, Corporate innovations and mergers and acquisitions, *Journal of Finance*, 69, 1923–1960
- Bhojra, S., Lee, Ch., Oler, D., 2003, What's My Line? A Comparison of Industry Classification Schemes for Capital Market Research, *Journal of Accounting Research*, 41(5), 745-774
- Bloom, N., Schankerman, M., Van Reenen, J., 2013, Identifying Technology Spillovers and Product Market Rivalry, *Econometrica*, 81(4), 1347-1393
- Bloom, N. , Lucking, B., Van Reenen, J., 2017, Have R&D Spillovers Changed?, *Working Paper*, Available at SSRN: <https://ssrn.com/abstract=3003576>
- Bowen III, D., Frésard, L., Hoberg, G., 2019, Technological Disruptiveness and the Evolution of IPOs and Sell-Outs, Working Paper, Available at SSRN: <https://ssrn.com/abstract=3245839>
- Bustamante, C., Frésard, L., 2020, Does Firm Investment Respond to Peers' Investment?, *Management Science*, forthcoming
- Chang, X., Fu, K. Low, A., and Zhang, W., 2015, Non-executive employee stock options and corporate innovation, *Journal of Financial Economics*, 115, 168-188
- Chen, I., Hsu, P., Officer, M., Wang, Y., 2016, The Oscar Goes To...: Takeovers and Innovation Envy, Working Paper, Available at SSRN: <http://ssrn.com/abstract=2815148>
- Chen, Ch., Wu, X., 2019, Do U.S. Firms Innovate to Escape Neck-and-Neck Competition?, Working Paper, Available at SSRN: <https://ssrn.com/abstract=3436761>
- Cohen, L., Diether, K., Malloy, C., 2013, Misvaluing Innovation, *Review of Financial Studies*, 26, 635–666
- Cunningham, C., Ederer, Fl., Ma, S., 2020, Killer Acquisitions, Working Paper, Available at SSRN: <https://ssrn.com/abstract=3241707>
- Davis J., Fama E. French E, 2000, Characteristics, Covariances, and Average Returns: 1929-1997, *Journal of Finance*, 55(1), 389-406
- Doidge, C., Karolyi, G. A., Stulz, R., 2017, The U.S. listing gap, *Journal of Financial Economics*, 123(3), 464-487

- Eckbo, B. E., T. Makaew, and K. S. Thorburn, 2018, Are stock-financed takeovers opportunistic?, *Journal of Financial Economics*, 128(3), 443–465
- Fama, E.F., 1991. Efficient Capital Markets:II, *Journal of Finance*, 46(5), 1575-1617
- Fama, E.F., French, K.R., 1998, Taxes, Financing Decisions, and Firm Value, *Journal of Finance*, 53(3), 819-843
- Foucault, T., Frésard, L., 2014, Learning from Peers’ Stock Prices and Corporate Investment, *Journal of Financial Economics*, 111, 554-577
- Frame, W., White, L., 2004, Empirical studies of financial innovation: lots of talk, little action?, *Journal of Economic Literature*, 42, 116–144
- Frattaroli, M., 2020, Does protectionist anti-takeover legislation lead to managerial entrenchment?, *Journal of Financial Economics*, 136, 105-136
- Fulghieri, P., M. Sevilir, M., 2009, Organization and financing of innovation, and the choice between corporate and independent venture capital, *Journal of Financial and Quantitative Analysis*, 44, 601–644
- Fuller, K., Netter, J., Stegemoller, M., 2002, What Do Returns to Acquiring Firms Tell Us? Evidence from Firms that Make Many Acquisitions, *Journal of Finance*, 57(4), 1763-1793
- Gao, H., Hsu, P., Li, K., 2018, Innovation Strategy of Private Firms, *Journal of Financial and Quantitative Analysis*, 53(1), 1-32
- Granja, J., Moreira, S., 2019, Product Innovation and Credit Market Disruptions, Working Paper Available at SSRN: <https://ssrn.com/abstract=3477726>
- Hall, B., Jaffe, A. Trajtenberg, M., 2001, The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools, NBER Working Paper 8498
- Haucap, J., Rasch, A., Stiebale, J., 2019, How mergers affect innovation: Theory and evidence, *International Journal of Industrial Organization*, 63, 283-325
- He, J. and Tian, X., 2013, The dark side of analyst coverage: The case of innovation, *Journal of Financial Economics*, 109, 856-878
- Hirshleifer, D., Low, A. Teoh, S., 2012, Are Overconfident CEOs Better Innovators? *Journal of Finance* 67(4), 1457-1498
- Hirshleifer, D., Hsu, P., Li, D., 2013, Innovative Efficiency and Stock Returns, *Journal of Financial Economics*, 107(3), 632-654
- Hirshleifer, D., Hsu, P., Li, D., 2018, Innovative Originality, Profitability, and Stock Returns, *Review of Financial Studies*, 31(7), 2253-2605
- Hoberg, G., Phillips, G., 2010, Product market synergies and competition in mergers and acquisitions: A text-based analysis. *Review of Financial Studies* 23,3773–3811
- Hoberg, G., Phillips, G., 2016, Text-based network industries and endogenous product differentiation, *Journal of Political Economy* ,124, 1423–1465
- Hombert, J., Matray, A., 2018, Can Innovation Help U.S. Manufacturing Firms Escape Import Competition from China?, *Journal of Finance*, 73(5), 2003-2039
- Holmstrom, B., 1989, Agency costs and innovation, *Journal of Economic Behavior and Organization*, 12, 305-327
- Jaffe, A., 1986, Technological Opportunity and Spillovers of R&D: Evidence From Firms’ Patents, Profits and Market Value, *American Economic Review*, 76, 984–1001
- Jiang W., 2017, Have Instrumental Variables Brought Us Closer to the Truth, *The Review of Corporate Finance Studies*, 6(2), 127–140
- Kamepalli, S., Rajan, R., Zingales, L., 2020, Kill Zone, University of Chicago, Becker Friedman Institute for Economics Working Paper No. 2020-19. Available at SSRN: <https://ssrn.com/abstract=3555915>

- Koh, P.S., Reeb, D.M., Sojli, E., Tham, W.W., Wang, W., 2021, Deleting Unreported Innovation, *Journal of Financial and Quantitative Analysis*, forthcoming
- Knott, A.M., 2008, R&D/Returns Causality: Absorptive Capacity or Organizational IQ, *Management Science*, 54(12), 2054-2067
- Kogan, L., Papanikolaou, D., Seru, A. and Stoffman, N., 2017. Technological innovation, resource allocation, and growth, *Quarterly Journal of Economics*, 132(2), 665-712
- Lerner, Josh, Morten Sorensen, and Per Stromberg. 2011, Private Equity and Long-Run Investment: The Case of Innovation. *Journal of Finance*, 66, 445–477
- Lerner, J., Seru, A., 2017, The Use and Misuse of Patent Data: Issues for Corporate Finance and Beyond, NBER Working Paper No. w24053, Available at SSRN: <https://ssrn.com/abstract=3077781>
- Malmendier, U., Tate, G., 2008, Who Makes Acquisitions? CEO Overconfidence and the Market's Reaction, *Journal of Financial Economics*, 89, 20–43
- Matray, A., 2021, Matray, Adrien, The Local Innovation Spillovers of Listed Firms, *Journal of Financial Economics*, 141,395-412
- Osborne, M.J., 2003, *An Introduction to Game Theory*, New York: Oxford University Press
- Petersen, M., 2009, Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, *Review of Financial Studies*, 22, 435-480
- Phillips, G., Zhdanov, A., 2013, R&D and the incentives from merger and acquisition activity, *Review of Financial Studies*, 26, 34–78
- Rhodes-Kropf, M., Robinson, D., Viswanathan, S., 2005, Valuation waves and merger activity: the empirical evidence, *Journal of Financial Economics*, 77, 561-603
- Romer, P., 1990, Endogenous Technological Change, *Journal of Political Economy*, 98(5), S71-S102
- Schumpeter, Joseph A., 1943, *Capitalism, Socialism and Democracy*. (London: George Allen & Unwin)
- Seru, A., 2014, Firm boundaries matter: Evidence from conglomerates and R&D activity, *Journal of Financial Economics*, 111, 381-405
- Shapiro, C., 2012, Competition and Innovation: Did Arrow Hit the Bull's Eye? The Rate and Direction of Inventive Activity Revisited, Josh Lerner and Scott Stern, editors, University of Chicago Press, 361-404
- Stein, Jeremy C., 1989, Efficient Capital Markets, Inefficient Firms: A Model of Myopic Corporate Behavior, *Quarterly Journal of Economics* 104, 655-669
- Stock J.H., Watson, M.W., 2020, *Introduction to Econometrics*, 4th ed., Pearson, New-York
- Wilson, D. J., 2009, Beggar thy neighbor? The in-state, out-of-state and aggregate effects of R&D tax credits, *Review of Economics and Statistics* 91, 431–436

Figure 1 – Hypothesis and Predictions

Figure 1 put in relation the increase in rival innovation investments, the firm innovation investment reaction and its valuation consequence under the Innovation Arms Race hypothesis, the Schumpeter (1943) Rent Dissipation hypothesis and the Arrow (1962) Competition Escape hypothesis.

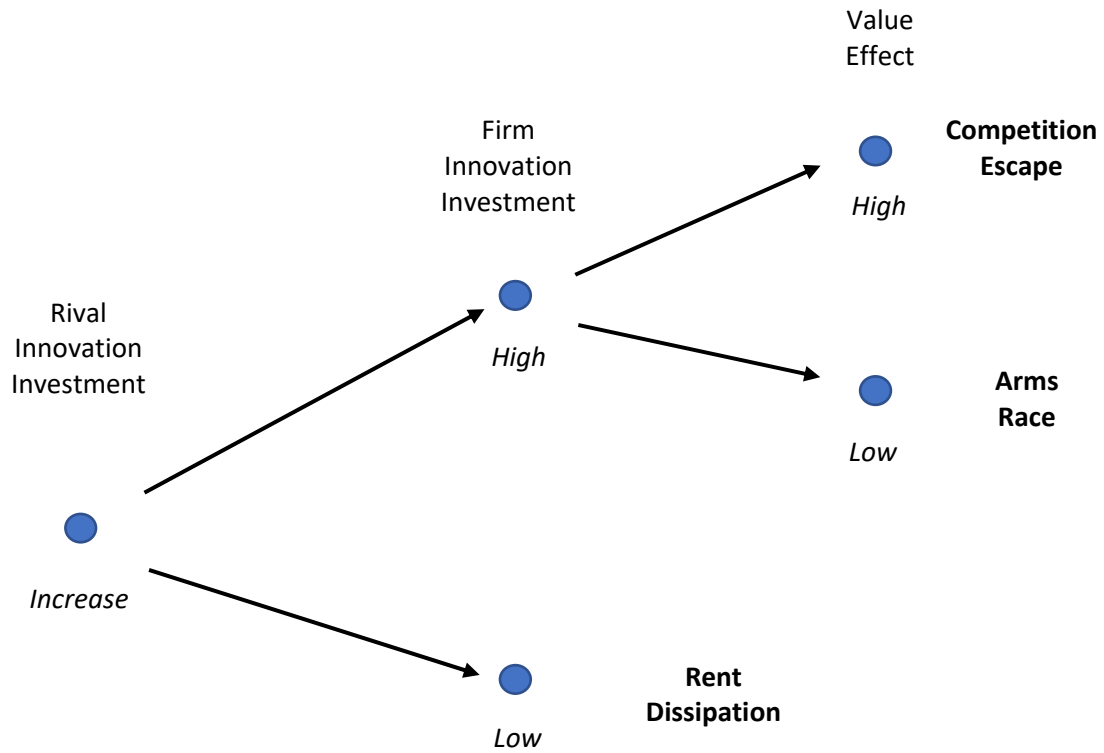


Table 1 – M&A Sample

Table 1 presents sample statistics by year. In Column 1, the number of unique acquirers in the M&A sample is provided. Columns 2 and 3 display the number of M&A transactions and the corresponding aggregate deal value respectively. Columns 4 and 5 show the number of innovative target acquisitions (see Section 3.1 for innovative acquisition definition) and the corresponding aggregate deal value respectively while Columns 6 and 7 provide the corresponding statistics of listed targets only.

Year	All M&A Deals			All Innovative Targets		Public Innovative Targets	
	1	2	3	4	5	6	7
	Unique Acquirers	Numbers	Dollar Value [In Billions]	Numbers	Dollar Value [In Billions]	Numbers	Dollar Value [In Billions]
1996	1261	3006	291.07	722	29.31	48	7.80
1997	1449	3601	362.81	747	38.04	125	22.78
1998	1522	3843	688.65	959	92.78	157	55.37
1999	1369	3317	819.82	892	239.68	150	200.30
2000	1248	2714	859.05	915	166.46	137	75.48
2001	988	1842	332.95	562	37.11	106	20.82
2002	883	1563	175.28	460	30.72	76	11.39
2003	860	1523	156.12	446	40.18	69	12.69
2004	946	1714	263.29	526	55.72	41	28.00
2005	976	1931	491.32	558	97.16	60	25.52
2006	1026	1992	486.12	239	73.91	34	38.78
2007	950	1959	472.68	252	76.39	45	31.16
2008	840	1640	291.31	209	30.95	44	25.35
2009	654	1239	413.56	225	139.04	47	53.04
2010	751	1475	305.00	196	29.14	22	8.30
2011	801	1587	401.00	213	68.22	28	49.64
2012	802	1624	293.96	192	50.56	25	22.96
2013	752	1444	311.46	176	26.10	15	14.16
2014	870	1665	704.77	184	95.65	20	53.81
2015	797	1504	868.53	151	104.60	25	82.78
2016	742	1405	623.88	160	66.85	14	14.45
2017	732	1352	538.10	167	63.07	16	41.18
2018	711	1337	766.01	123	42.91	11	13.44
2019	636	1141	795.95	62	22.55	7	3.60
Total	6,413	46,418	11,713	9,336	1,717	1,322	913

Table 2 – Descriptive Statistics

The table reports descriptive statistics for the set of variables used in our multivariate analyses. Panel A focuses on the correlated investment prediction tests and Panel B, on the value decrease tests. Columns 1 and 2 provides the arithmetic average and the standard deviation, Columns 3 to 5 the first, second and third quartiles of the distribution and Column 6, the number of observations. All variable definitions and data sources are provided in Section 3.2.

Variable Name	Mean	Stdev.	25th Pctl.	Median	75th Pctl.	Observations
	1	2	3	4	5	6
Panel A - Correlated Investment Tests						
<i>Dependent Variables</i>						
R&D Intensity	0.049	0.094	0.000	0.003	0.062	59568
Innovative Acquisition	0.091	0.464	0.000	0.000	0.000	59568
<i>Variables of Interest</i>						
RICI	0.180	0.309	0.000	0.000	0.250	59568
<i>Control Variables</i>						
Firm Size	6.029	2.143	4.446	5.955	7.513	59568
ROA	0.069	0.187	0.045	0.106	0.159	59568
Leverage	0.209	0.189	0.017	0.182	0.341	59568
Liquidity	0.131	0.151	0.022	0.076	0.185	59568
Intangible Ratio	0.165	0.194	0.002	0.086	0.268	59568
MTB	3.161	4.200	1.186	1.971	3.459	59568
Panel B - Value decrease Tests						
<i>Dependent Variables</i>						
lnMTBA	0.272	0.647	-0.160	0.199	0.642	35175
<i>Variables of Interest</i>						
RICI	0.168	0.295	0.000	0.000	0.250	35175
Excess R&D	-0.001	0.035	-0.001	0.000	0.000	35175
Excess Innovative Acquisition	0.000	0.019	0.000	0.000	0.000	35175
<i>Control Variables</i>						
R&D Intensity	0.042	0.078	0.000	0.004	0.054	35175
Innovative Acquisition	0.098	0.466	0.000	0.000	0.000	35175
Historical R&D	0.042	0.076	0.000	0.004	0.056	35175
Historical Innovative Acquisition	0.013	0.041	0.000	0.000	0.001	35175
E_{it}/A_{it}	0.022	0.176	0.011	0.055	0.089	35175
dE_{it}/A_{it}	0.013	0.272	-0.025	0.010	0.043	35175
dE_{it+2}/A_{it}	0.013	0.268	-0.029	0.010	0.052	35175
dA_{it}/A_{it}	0.083	0.429	-0.032	0.114	0.269	35175
dA_{t+2}/A_t	0.235	0.809	-0.048	0.106	0.312	35175
dRD_{it}/A_{it}	0.002	0.056	0.000	0.000	0.004	35175
dRD_{it+2}/A_{it}	0.007	0.063	0.000	0.000	0.004	35175
I_{it}/A_{it}	0.013	0.015	0.001	0.009	0.019	35175
dI_{it}/A_{it}	0.001	0.014	-0.002	0.000	0.003	35175
dI_{it+2}/A_{it}	0.003	0.027	-0.002	0.000	0.004	35175
D_{it}/A_{it}	0.012	0.037	0.000	0.000	0.014	35175
dD_{it}/A_{it}	0.002	0.045	0.000	0.000	0.001	35175
dD_{it+2}/A_{it}	0.002	0.040	0.000	0.000	0.002	35175
dV_{it+2}/A_{it}	0.403	2.277	-0.205	0.131	0.623	35175

Table 3 - Innovation Arms Race Correlated Investment and Value decrease Predictions Test

Table 3 reports results of Innovation Arms Race Predictions (see Figure 1). Columns 1 to 4 are dedicated to The Correlated Investment Prediction (incentives to innovate). The dependent variables are *R&D Intensity* in Columns 1 and 3, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Columns 2 and 4, defined as the number of innovative target acquisitions divided by the number of acquisitions by subject firm. The variable of interest is *RICI*, defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (see Equation 1). In Columns 1 and 2, *Innovative Acquisition* and *R&D Intensity* are included as control variable and in Columns 3 and 4, they are excluded as a robustness check. Columns 5 and 6 display tests of the Value decrease Prediction. The dependent variable is natural logarithm of one plus the ratio of the difference between the market value and the book value of assets scaled by the book value of assets, as in Fama and French (1992). The variables of interest are the interaction between *RICI* and *Excess R&D* or *Excess Innovative Acquisition*. *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Column 5 reports the results for the interaction between *RICI* and *Excess R&D* and Column 6, the results for the interaction between *RICI* and *Excess Innovative Acquisition*. Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

<i>Subject Firms'</i>	R&D	Innovative	R&D	Innovative	Market Value	
	Intensity	Acquisition	Intensity	Acquisition	5	6
	1	2	3	4		
RICI	0.008***	0.122***	0.008***	0.122***	0.032*	0.050**
	0.001	0.000	0.001	0.000	0.061	0.030
RICI x Excess R&D					-0.630**	
					0.032	
RICI x Historical R&D					0.120	
					0.645	
RICI x Excess Innovative Acquisition						-0.062***
						0.000
RICI x Historical Innovative Acquisition						-0.042**
						0.015
Innovative Acquisition	-0.001				0.028***	0.055***
	0.161				0.004	0.000
R&D Intensity		-0.093			1.597***	1.495***
		0.132			0.000	0.000
<i>Control Variables</i>	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59568	59568	59568	59568	35175	35175
Adjusted R ²	0.816	0.195	0.816	0.194	0.712	0.712

Table 4 – Innovation Arms Race Correlated Investment and Value decrease Predictions Test – Subsample Analyses

Table 4 replicates Table 3 tests of the Innovation Arms Race predictions (see Figure 1) and tests are performed for sub-samples of M&A transactions. In Panel A, the M&A sample is restricted to change of control transactions. Panel B reports the results when we take into account the innovative acquisitions of public target only and in Panel C, we limit our sample to horizontal transactions. In each panel, Columns 1 and 2 are dedicated to The Correlated Investment Prediction (incentives to innovate). The dependent variables are *R&D Intensity* in column 1, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Column 2, defined as the number of innovative target acquisitions divided by the number of acquisitions by subject firm. Columns 3 and 4 display tests of the Value decrease Prediction . The dependent variable is natural logarithm of one plus the ratio of the difference between the market value and the book value of assets scaled by the book value of assets, as in Fama and French (1992). The variables of interest are the interaction between *RICI* and *Excess R&D* or *Excess Innovative Acquisition*. *RICI* is defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (see Equation 1). *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Column 3 reports the results for the interaction between *RICI* and *Excess R&D* and Column 4, the results for the interaction between *RICI* and *Excess Innovative Acquisition*. Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

Panel A - Change of Control Transactions

<i>Subject Firms'</i>	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RICI	0.008*** 0.001	0.114*** 0.000	0.035** 0.040	0.049** 0.020
RICI x Excess R&D			-0.632** 0.031	
RICI x Historical R&D			0.080 0.754	
RICI x Excess Innovative Acquisition				-0.071*** 0.000
RICI x Historical Innovative Acquisition				-0.043** 0.038
Innovative Acquisition	-0.001* 0.095		0.026** 0.010	0.057*** 0.000
R&D Intensity		-0.103* 0.079	1.620*** 0.000	1.514*** 0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	58112	58112	34393	34393
Adjusted R ²	0.816	0.189	0.711	0.711

Panel B - Acquisitions of Public Targets Only

<i>Subject Firms'</i>	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4
RICI	0.003	0.007**	-0.012	-0.004
	0.144	0.050	0.500	0.722
RICI x Excess R&D			-0.969**	
			0.034	
RICI x Historical R&D			0.101	
			0.569	
RICI x Excess Innovative Acquisition				0.007
				0.881
RICI x Historical Innovative Acquisition				0.032
				0.543
Innovative Acquisition			-0.005	-0.004
			0.833	0.872
R&D Intensity			1.558***	1.514***
			0.000	0.000
<i>Control Variables</i>				
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	59568	59568	35175	35175
Adjusted R ²	0.816	0.041	0.711	0.711

Panel C - Horizontal Transactions

<i>Subject Firms'</i>	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4
RICI	0.009***	0.110***	0.015	0.017
	0.000	0.000	0.345	0.371
RICI x Excess R&D			-0.623**	
			0.028	
RICI x Historical R&D			0.044	
			0.851	
RICI x Excess Innovative Acquisition				-0.023
				0.170
RICI x Historical Innovative Acquisition				0.009
				0.622
Innovative Acquisition	-0.002**		0.016**	0.028**
	0.036		0.041	0.046
R&D Intensity		-0.116**	1.637***	1.537***
		0.042	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	45406	45406	28314	28314
Adjusted R ²	0.812	0.203	0.707	0.707

Table 5 – Innovation Arms Race Correlated Investment and Value decrease Predictions Test – Sector Level Analyses

Table 5 replicates Table 3 tests of the Innovation Arms Race predictions (see Figure 1) and tests are performed by sector. We use the Fama-French 5 industry classification, based on the correspondence table with 4-digit SIC codes provided by the authors. Panel A focuses on *consumer*, Panel B on *manufacturing*, Panel C on *high-tech*, Panel D on *Healthcare* and Panel E on *Other*. In each panel, Columns 1 and 2 are dedicated to The Correlated Investment Prediction (incentives to innovate). The dependent variables are *R&D Intensity* in column 1, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Column 2, defined as the number of innovative target acquisitions divided by the number of acquisitions by subject firm. Columns 3 and 4 display tests of the Value decrease Prediction. The dependent variable is natural logarithm of one plus the ratio of the difference between the market value and the book value of assets scaled by the book value of assets, as in Fama and French (1992). The variables of interest are the interaction between *RICI* and *Excess R&D* or *Excess Innovative Acquisition*. The variable of interest is *RICI* is defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (see Equation 1). *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Column 3 reports the results for the interaction between *RICI* and *Excess R&D* and Column 4, the results for the interaction between *RICI* and *Excess Innovative Acquisition*. Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

Panel A – Consumer

<i>Subject Firms'</i>	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RICI	0.002	0.010	0.064**	0.048
	0.380	0.437	0.040	0.138
RICI x Excess R&D			-1.604	
			0.364	
RICI x Historical R&D			-1.606	
			0.183	
RICI x Excess Innovative Acquisition				-0.058
				0.406
RICI x Historical Innovative Acquisition				-0.192
				0.102
Innovative Acquisition	-0.001		0.032	0.049**
	0.375		0.160	0.049
R&D Intensity		-0.174	3.482***	3.120***
		0.370	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	11974	11974	7385	7385
Adjusted R ²	0.783	0.150	0.763	0.763

Panel B - Manufacturing

<i>Subject Firms'</i>	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RICI	0.001	0.017	0.021	0.014
	0.533	0.359	0.492	0.561
RICI x Excess R&D			-0.267	
			0.788	
RICI x Historical R&D			0.088	
			0.892	
RICI x Excess Innovative Acquisition				-0.031
				0.511
RICI x Historical Innovative Acquisition				0.102
				0.194
Innovative Acquisition	0.000		0.033*	0.038**
	0.789		0.058	0.049
R&D Intensity		0.040	2.795***	2.749***
		0.792	0.001	0.001
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	14585	14585	9350	9350
Adjusted R ²	0.778	0.157	0.708	0.709

Panel C - High-Tech

<i>Subject Firms'</i>	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RICI	0.010***	0.148***	-0.011	0.015
	0.002	0.001	0.721	0.579
RICI x Excess R&D			-0.197	
			0.544	
RICI x Historical R&D			0.171	
			0.547	
RICI x Excess Innovative Acquisition				-0.034*
				0.072
RICI x Historical Innovative Acquisition				-0.031
				0.305
Innovative Acquisition	-0.001		0.008	0.026**
	0.310		0.287	0.017
R&D Intensity		-0.117	0.999***	1.001***
		0.287	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	16586	16586	9362	9362
Adjusted R ²	0.746	0.201	0.695	0.695

Panel D - Health

<i>Subject Firms'</i>	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RICI	0.011**	0.048	-0.016	0.007
	0.035	0.163	0.613	0.802
RICI x Excess R&D			-0.837*	
			0.084	
RICI x Historical R&D			0.092	
			0.720	
RICI x Excess Innovative Acquisition				-0.035
				0.317
RICI x Historical Innovative Acquisition				-0.047
				0.185
Innovative Acquisition	-0.001		0.015	0.033
	0.518		0.335	0.177
R&D Intensity		-0.078	2.328***	2.131***
		0.515	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	5950	5950	3497	3497
Adjusted R ²	0.796	0.201	0.680	0.679

Panel E - Other

<i>Subject Firms'</i>	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RICI	0.002	0.094***	0.113**	0.082*
	0.412	0.003	0.030	0.099
RICI x Excess R&D			0.278	
			0.830	
RICI x Historical R&D			-0.455	
			0.443	
RICI x Excess Innovative Acquisition				-0.036
				0.528
RICI x Historical Innovative Acquisition				0.135**
				0.014
Innovative Acquisition	-0.004**		0.147***	0.153***
	0.047		0.000	0.001
R&D Intensity		-0.500*	0.709	0.716
		0.083	0.310	0.307
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	10039	10039	5405	5405
Adjusted R ²	0.896	0.158	0.733	0.733

Table 6 – Innovation Arms Race – Within-Industry Results

Table 6 reports the results of the Innovation Arms Race predictions (see Figure 1) depending on the characteristics of industry participants. Panel A reports the results for Leader and Laggard firms and Panel B reports the results for Neck-to-Neck firms. In each panel, Columns 1 and 2 are dedicated to The Correlated Investment Prediction (incentives to innovate). The dependent variables are *R&D Intensity* in column 1, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Column 2, defined as the number of innovative target acquisitions divided by the number of acquisitions by subject firm. The variables of interest are the interaction between *RICI* and Leader or Laggard in panel A and the interaction between *RICI* and Neck-to-Neck firms in panel B. *RICI* is defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (see Equation 1). *Leader (Laggard)* is an indicator variable which is equal to 1 if the firm is in the *highest (lowest)* quartile of ROA and market shares. *Neck-to-Neck Firms* is an indicator variable which is equal to 1 if the rival firm is in the highest quartile of the yearly distribution of HP similarity score. In each panel, Columns 3 and 4 display tests of the Value decrease Prediction. The dependent variable is natural logarithm of one plus the ratio of the difference between the market value and the book value of assets scaled by the book value of assets, as in Fama and French (1992). The variables of interest are the interaction between *RICI and Excess R&D/Excess Innovative Acquisition* and *Leader/Laggard* in Panel A and the interaction between *RICI and Excess R&D/Excess Innovative Acquisition* and *Neck-to-Neck* firms in Panel B. *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

Panel A – Industry Leaders and Laggards

Subject Firms'	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RICI			0.033*	0.050**
			0.052	0.030
RICI x Leader	0.007***	0.217***		
	0.004	0.000		
RICI x Laggard	0.012***	0.059***		
	0.001	0.000		
RICI x Others	0.005**	0.109***		
	0.030	0.001		
RICI x Excess R&D x Leader			-1.909***	
			0.008	
RICI x Excess R&D x Laggard			-0.178	
			0.550	
RICI x Excess R&D x Others			-1.047**	
			0.029	
RICI x Excess IA x Leader				-0.066***
				0.000
RICI x Excess IA x Laggard				-0.053
				0.249
RICI x Excess IA x Others				-0.055**
				0.045
RICI x Historical IA			0.066	
			0.796	
RICI x Historical R&D				-0.042**
				0.013
Innovative Acquisition	-0.001		0.028***	0.056***
	0.183		0.005	0.000
R&D Intensity		-0.089	1.600***	1.495***
		0.155	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	59568	59568	35175	35175
Adjusted R ²	0.80	0.20	0.712	0.712
F-tests				
$\beta_{RICI \times Leader} - \beta_{RICI \times Laggard} \neq 0$	-0.005	0.158***		
	0.138	0.001		
$\beta_{RICI \times Excess R\&D \times Leader} - \beta_{RICI \times Excess R\&D \times Laggard} \neq 0$			-2.087**	
			0.011	
$\beta_{RICI \times Excess IA \times Leader} - \beta_{RICI \times Excess IA \times Laggard} \neq 0$				-0.199
				0.788

Panel B – Neck-to-Neck Firms

Subject Firms'	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RICI			0.030*	0.049**
			0.074	0.026
RICI x Neck-to-Neck	0.016***	0.169***		
	0.003	0.000		
RICI x Others	0.006***	0.110***		
	0.002	0.001		
RICI x Excess R&D x Neck-to-Neck			-0.801**	
			0.036	
RICI x Excess R&D x Others			-0.447	
			0.210	
RICI x Excess Innovative Acquisition x Neck-to-Neck				-0.080***
				0.000
RICI x Excess Innovative Acquisition x Others				-0.055***
				0.001
RICI x Historical Innovative Acquisition			0.132	
			0.627	
RICI x Historical R&D				-0.046**
				0.010
Innovative Acquisition	-0.001		0.028***	0.055***
	0.137		0.005	0.000
R&D Intensity		-0.099	1.602***	1.505***
		0.110	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	59568	59568	35175	35175
Adjusted R ²	0.816	0.195	0.712	0.712
F-tests				
$\beta_{RICI \times Neck-to-Neck} - \beta_{RICI \times Others} \neq 0$	0.010**	0.059		
	0.024	0.117		
$\beta_{RICI \times Excess R\&D Neck-to-Neck} - \beta_{RICI \times Excess R\&D Others} \neq 0$			-0.354	
			0.420	
$\beta_{RICI \times Excess IA \times Neck-to-Neck} - \beta_{RICI \times Excess IA \times Others} \neq 0$				-0.025**
				0.024

Table 7 – The Arms Race Hypothesis Correlated Investment Prediction – Instrumental Variable Estimates

Table 9 replicates Table 3 tests of the Innovation Arms Race Correlated Investment using an instrumental variable approach. The dependent variables are *R&D Intensity* in column 2, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Column 4, defined as the number of innovative target acquisitions divided by the number of acquisitions by subject firm. The variable of interest is *RICI*, defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (see Equation 1) and is instrumented by *Rival's Tax Induced R&D* (it is the predicted value of firm-level investment in R&D due to tax credit incentives and is obtained by from the Hall-Jorgenson user cost of R&D and replicating the procedure described in Bloom et al. (2013) Internet Appendix B.3.1, denoted $R\&DUC^{10NN}$). $R\&DUC$ is the firm tax induced used cost. Columns 1 and 3 report the results obtained from first stage regression and Columns 1 and 4 display the results from second stage regression. Estimates are obtained using 2SLS regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

	<i>1st Stage</i>	<i>2nd Stage</i>	<i>1st Stage</i>	<i>2nd Stage</i>
	RICI	R&D Intensity	RICI	Innovative Acquisition
	1	2	3	4
$R\&DUC^{10NN}$	-0.030*** 0.000		-0.031*** 0.000	
RICI		0.089** 0.035		1.348*** 0.000
Innovative Acquisition	0.039*** 0.000	-0.004** 0.016		
R&D Intensity			0.255*** 0.000	-0.463*** 0.004
$R\&DUC$	-0.0194*** 0.004	0.020*** 0.000	-0.022*** 0.000	0.036 0.118
Fisher test of significance F(9,6860)	42.20		39.77	
Prob >F	0.000		0.000	
Control Variables	Yes	Yes		Yes
Year Fixed Effects	Yes	Yes		Yes
Firm Fixed Effects	Yes	Yes		Yes
Observations	41660	41660	41660	41660
Overall R ²		0.392		0.040
Chi ²		696.67		119.77

Table 8 - M&A and Rivals' Incentives to Innovate – Innovation Efficiency

Table 8 reports results the effects of Innovation Arms Race on innovation efficiency. The dependent variables are *Number of Patents* in Columns 1 and 2 of panel A, defined as log of one plus number of patents, and *Number of Citations* in Columns 1 and 2 of panel B, defined as log of one plus number of citations. In both the panels, the variables of interest are the interaction between *RICI* and *Excess R&D* or *Excess Innovative Acquisition*. *RICI* is defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (see Equation 1). *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Column 1 reports the results for the interaction between *RICI* and *Excess R&D* and Column 2, the results for the interaction between *RICI* and *Excess Innovative Acquisition*. Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

Panel A – Patents based

<i>Subject Firms'</i>	Number of Patents	
	1	2
RICI	0.000	0.025
	0.985	0.275
RICI x Excess R&D	0.280	
	0.247	
RICI x Historical R&D	0.250	
	0.208	
RICI x Excess Innovative Acquisition		-0.003
		0.818
RICI x Historical Innovative Acquisition		-0.001
		0.861
Innovative Acquisition	0.006	0.007
	0.235	0.211
R&D Intensity	-0.099	0.044
	0.509	0.758
Control Variables	Yes	Yes
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	4147	4147
Adjusted R ²	0.92	0.92

Panel B – Citation based

<i>Subject Firms'</i>	Number of Citations	
	1	2
RICI	-0.037	-0.027
	0.425	0.432
RICI x Excess R&D	0.028	
	0.912	
RICI x Historical R&D	0.109	
	0.586	
RICI x Excess Innovative Acquisition		0.039**
		0.026
RICI x Historical Innovative Acquisition		0.016
		0.406
Innovative Acquisition	-0.002	-0.023**
	0.777	0.043
R&D Intensity	0.361	0.378*
	0.109	0.055
Control Variables	Yes	Yes
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	6212	6212
Adjusted R ²	0.76	0.76

Table 9 – Innovation Arms Race Correlated Investment and Value decrease Predictions Test – Extensive Margin Analyses

Table 4 displays results of Innovation Arms Race Predictions (see Figure 1). In contrast with Table 3, tests are performed at the extensive margin (the sample of firms include firms that are not subject to rival innovative acquisition pressure) Columns 1 and 2 are dedicated to The Correlated Investment Prediction (incentives to innovate). The dependent variables are *R&D Intensity* in column 1, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Column 2, defined as the number of innovative target acquisitions divided by the number of acquisitions by subject firm. The variable of interest is *RICI*, defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (see Equation 1). Columns 3 and 4 display tests of the Value decrease Prediction . The dependent variable is natural logarithm of one plus the ratio of the difference between the market value and the book value of assets scaled by the book value of assets, as in Fama and French (1992). The variables of interest are the interaction between *RICI* and *Excess R&D* or *Excess Innovative Acquisition*. *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Column 3 reports the results for the interaction between *RICI* and *Excess R&D* and Column 4, the results for the interaction between *RICI* and *Excess Innovative Acquisition*. Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

<i>Subject Firms'</i>	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RICI	0.005**	0.111***	0.035**	0.042**
	0.030	0.000	0.025	0.037
RICI x Excess R&D			-0.607**	
			0.013	
RICI x Historical R&D			-0.002	
			0.993	
RICI x Excess Innovative Acquisition				-0.066***
				0.000
RICI x Historical Innovative Acquisition				-0.047***
				0.008
Innovative Acquisition	-0.001		0.028***	0.057***
	0.146		0.002	0.000
R&D Intensity		-0.064	1.402***	1.298***
		0.122	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	81375	81375	47011	47011
Adjusted R ²	0.818	0.203	0.709	0.709

Appendix A.1: Variable Definitions

The table provides the definition of the set of variables used in our multivariate analyses. Panel A focuses on the variables used in correlated investment prediction tests and Panel B, on the variables used in value decrease tests.

Variable Name	Definitions
Panel A - Correlated Investment Tests	
<i>Dependent Variables</i>	
R&D Intensity	It is defined as R&D expenses divided by total assets (<i>Source: Compustat and CRSP</i>).
Innovative Acquisition	It is defined as the number of innovative target acquisitions divided by the number of acquisitions by subject firm (<i>Source: SDC</i>).
<i>Variables of Interest</i>	
RICI	It is defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (<i>Source: SDC</i>).
<i>Control Variables</i>	
Firm Size	It is defined as the natural logarithm of total assets (<i>Source: Compustat and CRSP</i>).
ROA	It is defined as the ratio of operating income before depreciation to total assets (<i>Source: Compustat and CRSP</i>).
Leverage	It is defined as the ratio of long-term debt and debt in current liabilities to total assets (<i>Source: Compustat and CRSP</i>).
Liquidity	It is a cash ratio and is defined as the ratio of cash position to total assets (<i>Source: Compustat and CRSP</i>).
Intangible Ratio	It is defined as the ratio of intangible assets to total assets (<i>Source: Compustat and CRSP</i>).
MTB	It is defined as the ratio of market value of equity to book value equity, with book equity computed as in Davis et al., 2000 (<i>Source: Compustat and CRSP</i>).
Panel B - Value decrease Tests	
<i>Dependent Variables</i>	
Firm Value	It is the logarithm of one plus the market valuation ratio introduced in Fama and French (1998), which is the difference between the market value and book value of total assets scaled by the book value of total assets (<i>Source: Compustat and CRSP</i>).
<i>Variables of Interest</i>	
RICI	It is defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (<i>Source: SDC</i>).
Excess R&D	It is defined as the difference between R&D Intensity of the subject firm and its historical R&D Intensity (the average R&D Intensity over the last three years) (<i>Source: Compustat and CRSP</i>).
Excess Innovative Acquisition	It is defined as the difference between Innovative Acquisition of the subject firm and its historical Innovative Acquisition (the average Innovative Acquisition over the last three years) (<i>Source: SDC</i>).
<i>Control Variables</i>	

R&D Intensity	It is defined as R&D expenses divided by total assets (<i>Source: Compustat and CRSP</i>).
Innovative Acquisition	It is defined as the number of innovative target acquisitions divided by the number of acquisitions by subject firm (<i>Source: SDC</i>).
Historical R&D	It is defined as (the average R&D Intensity over the last three years) (<i>Source: Compustat and CRSP</i>).
Historical Innovative Acquisition	It is defined as the average Innovative Acquisition over the last three years (<i>Source: SDC</i>).
E_{it}/A_{it}	It is the current earnings variable and is defined as earnings in year t scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).
dE_{it}/A_{it}	It is the past earnings variable and is defined as change in earnings ($E_{it} - E_{it-2}$) scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).
dE_{it+2}/A_{it}	It is the future earnings variable and is defined as change in earnings ($E_{it+2} - E_{it}$) scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).
dA_{it}/A_{it}	It is the past changes in assets and is defined as change in assets ($A_{it} - A_{it-2}$) scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).
dA_{it+2}/A_{it}	It is the future changes in assets and is defined as change in assets ($A_{it+2} - A_{it}$) scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).
dRD_{it}/A_{it}	It is the past changes in research and development expenses and is defined as change in assets ($RD_{it} - RD_{it-2}$) scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).
dRD_{it+2}/A_{it}	It is the future changes in research and development expenses and is defined as change in assets ($RD_{it+2} - RD_{it}$) scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).
I_{it}/A_{it}	It is the current interest variable and is defined as interest expense in year t scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).
dI_{it}/A_{it}	It is the past interest variable and is defined as change in interest expenses ($I_{it} - I_{it-2}$) scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).
dI_{it+2}/A_{it}	It is the future interest variable and is defined as change in interest expenses ($I_{it+2} - I_{it}$) scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).
D_{it}/A_{it}	It is the current dividend variable and is defined as dividends in year t scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).
dD_{it}/A_{it}	It is the past dividend variable and is defined as change in dividend ($D_{it} - D_{it-2}$) scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).
dD_{it+2}/A_{it}	It is the future dividend variable and is defined as change in dividend expenses ($D_{it+2} - D_{it}$) scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).
dV_{it+2}/A_{it}	It the future firm value variable and is defined as change in market value ($MV_{it+2} - MV_{it}$) scaled by book value of assets in year t (<i>Source: Compustat and CRSP</i>).

Appendix A.2: Innovation Arms Race Process Anticipations

The econometric specifications that we introduce in Equations 8 and 9 to test the value decrease prediction assume that the start of an innovation arms' race process has not been (fully) anticipated by investors. To test this assumption, we investigate whether we observe a difference in investor reactions to announcements of innovative and non-innovative acquisitions by rivals. Such a difference, if negative, would indeed reveal that investors anticipate less value creation (or more value destruction) in case of innovative rival acquisition, consistently with the start of damaging arms' race between industry participants.

We start by collecting all M&A transactions by product market space 10 nearest neighbor rivals for our sample of 6,413 acquirers (see Table 1), the firms under focus. For each firm-year-rival, we keep only the first acquisition and for each acquirers, we test whether there has been at least one rival innovative acquisitions. This procedure leads to a sample of 81,942 firm-year-rival acquisitions.

We next compute firm under focus cumulative abnormal returns (CAR) around these 81,942 events. CAR are obtained using Wharton Research Data Service (WRDS) daily event study tool with the market model as return generating process, a 250 days estimation window with a minimum of 100 available returns, a 40 days gap between then end of the estimation window and the announcement to avoid contamination by rumors and anticipations, and 3 days and 7 days centered event window for robustness checks.

We finally regress firm under focus CAR on a dummy variable D_{it} equal to one in case of rival innovative acquisition using the following specification :

$$CAR_{it} = \alpha_i + \beta_t + \gamma D_{it} + \epsilon_{it} \quad (\text{A.2.1})$$

where α_i are firm under focus fixed effects and β_t are year fixed effects. Under the null hypothesis of absence of investor antiaptions of the start of an arms' process, we expect γ to be equal to zero.

Results are reported in Table A.2 and are without ambiguities. In the absence of fixed effects (Column 1), whether using a 3 days centered event window (Panel A) or a 7 days one (Panel B), the γ coefficient is positive and statistically significant. This is inconcistent with investors anticipating the start of an innovation arms race process, because anticipations should lead to less value creation, not more. Once fixed effects are introduced, the estimated γ coefficient loses its statistical significance, a result that can not be attributed to a weak statistical power issue in the light the our sample size. It is worthwhile to note that year fixed effects are already enough to generate this results. Apparently, the statistically significant

difference in CAR between innovative and non-innovative rival acquisitions is driven by some time-varying common latent factors.

Table A.2 - Innovation Arms Race – Investor Anticipation Analyses

The table reports the results from the tests whether investors anticipate the start of an Innovation Arms Race. The dependent variable is CAR(-1, +1) and corresponds to the subject firm's cumulative abnormal return computed over a 3-day window (-1, +1) around the announcement day of the deal. The abnormal return is computed using a market model with parameters estimated over the estimation period (-250, -40) with respect to the announcement day. The variable of interest is Rival's Innovative Acquisition. Estimates are obtained using a linear regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

<i>Subject Firms'</i>	CAR (-1, +1)			
	1	2	3	4
Rival's Innovative Acquisition	0.245*** 0.002	0.097 0.216	-0.007 0.940	-0.016 0.861
Year Fixed Effects		Yes	Yes	Yes
Industry Fixed Effects			Yes	
Firm Fixed Effects				Yes
Observations	81942	81942	81942	81942
Adjusted R ²	0.0002	0.0046	0.0135	0.0542

Internet Appendix

This internet appendix reports additional results to accompany the paper "*Innovation Arms Race*".

The contents are as follows:

Table I.A. 1 reports the baseline results from the Table 3 in the paper and shows the coefficients of all the respective control variables used in each regression model.

Table I.A. 2 reports the baseline results from Table 3 in the paper, with the variable interest based on value of transactions (*RIVI*).

Table I.A. 3 reports the baseline results from Table 4 in the paper, with the variable interest based on value of transactions (*RIVI*).

Table I.A. 4 reports the baseline results from Table 5 in the paper, with the variable interest based on value of transactions (*RIVI*).

Table I.A. 5 reports the baseline results from Table 6 in the paper, with the variable interest based on value of transactions (*RIVI*).

Table I.A. 6 reports the baseline results from Table 7 in the paper, with the variable interest based on value of transactions (*RIVI*).

Table I.A. 7 reports the baseline results from Table 8 in the paper, with the variable interest based on value of transactions (*RIVI*).

Table I.A. 8 reports the baseline results from Table 9 in the paper, with the variable interest based on value of transactions (*RIVI*).

Table I.A. 9 - reports the baseline results from Table 3 in the paper, with the addition of Industry x Year Fixed Effects.

Table I.A. 10 - reports the baseline results from Table 3 in the paper, with the with the variable interest alternatively defined (*RIAT*).

Table I.A. 11 tests The Correlated Investment Prediction (incentives to innovate) using multiple imputation analysis.

Table I.A. 1 - Innovation Arms Race

Table I.A. 1 reports results of Innovation Arms Race Predictions (see Figure 1). In contrast with Table 3 in the paper, the table displays the results with full set of controls we include in respective regression models. Columns 1 to 4 are dedicated to The Correlated Investment Prediction (incentives to innovate). The dependent variables are *R&D Intensity* in Columns 1 and 3, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Columns 2 and 4, defined as the number of innovative target acquisitions divided by the number of acquisitions by subject firm. The variable of interest is *RICI*, defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (see Equation 1). In Columns 1 and 2, *Innovative Acquisition* and *R&D Intensity* are included as control variable and in Columns 3 and 4, they are excluded as a robustness check. Columns 5 and 6 display tests of the Value decrease Prediction. The dependent variable is natural logarithm of one plus the ratio of the difference between the market value and the book value of assets scaled by the book value of assets, as in Fama and French (1992). The variables of interest are the interaction between *RICI* and *Excess R&D* or *Excess Innovative Acquisition*. *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Column 5 reports the results for the interaction between *RICI* and *Excess R&D* and Column 6, the results for the interaction between *RICI* and *Excess Innovative Acquisition*. Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

<i>Subject Firms'</i>	R&D	Innovative	R&D	Innovative	Firm Value	
	Intensity	Acquisition	Intensity	Acquisition	5	6
	1	2	3	4		
RICI	0.008***	0.122***	0.008***	0.122***	0.032*	0.050**
	0.001	0.000	0.001	0.000	0.061	0.030
RICI x Excess R&D					-0.630**	
					0.032	
RICI x Historical R&D					0.120	
					0.645	
RICI x Excess Innovative Acquisition						-0.062***
						0.000
RICI x Historical Innovative Acquisition						-0.042**
						0.015
Innovative Acquisition	-0.001				0.028***	0.055***
	0.161				0.004	0.000
R&D Intensity		-0.093			1.597***	1.495***
		0.132			0.000	0.000
<i>Control Variables</i>						
Firm Size	-0.009***	-0.006	-0.009***	-0.005		
	0.000	0.434	0.000	0.500		
ROA	-0.077***	0.041*	-0.077***	0.049**		
	0.000	0.093	0.000	0.032		
Leverage	-0.012***	-0.107***	-0.011***	-0.106***		
	0.002	0.000	0.002	0.000		
Liquidity	0.007	-0.003	0.007	-0.003		
	0.139	0.921	0.139	0.903		
Intangible Ratio	-0.009**	-0.182***	-0.009**	-0.181***		

	0.045	0.000	0.050	0.000		
MTB	0.000	0.002**	0.000	0.002**		
	0.127	0.034	0.125	0.028		
E_{it}/A_{it}					0.449***	0.454***
					0.000	0.000
dE_{it}/A_{it}					0.070**	0.069**
					0.015	0.017
dE_{it+2}/A_{it}					0.087***	0.087***
					0.005	0.005
dA_{it}/A_{it}					0.121***	0.126***
					0.000	0.000
dA_{it+2}/A_{it}					0.219***	0.220***
					0.000	0.000
dRD_{it}/A_{it}					0.072	0.028
					0.536	0.811
dRD_{it+2}/A_{it}					0.791***	0.795***
					0.000	0.000
l_{it}/A_{it}					-1.591*	-1.533*
					0.068	0.081
dl_{it}/A_{it}					0.008	-0.036
					0.989	0.948
dl_{it+2}/A_{it}					-0.935*	-0.929*
					0.079	0.083
D_{it}/A_{it}					1.523***	1.521***
					0.000	0.000
dD_{it}/A_{it}					0.072	0.074
					0.656	0.647
dD_{it+2}/A_{it}					0.750***	0.751***
					0.001	0.001
dV_{it+2}/A_{it}					-0.069***	-0.069***
					0.000	0.000
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59568	59568	59568	59568	35175	35175
Adjusted R ²	0.816	0.195	0.816	0.194	0.712	0.712

Table I.A. 2 - Innovation Arms Race

Table I.A. 2 reports results of Innovation Arms Race Predictions (see Figure 1). In contrast with Table 3 in the paper, the variable of interest is based on the dollar value of transaction. Columns 1 to 4 are dedicated to The Correlated Investment Prediction (incentives to innovate). The dependent variables are *R&D Intensity* in Columns 1 and 3, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Columns 2 and 4, defined as the dollar value of innovative target acquisitions divided by the total value of acquisitions by subject firm. The variable of interest is *RIVI*, defined as the dollar value of innovative target acquisitions divided by the total dollar value of acquisitions by rival firms per year (see Equation 1). In Columns 1 and 2, *Innovative Acquisition* and *R&D Intensity* are included as control variable and in Columns 3 and 4, they are excluded as a robustness check. Columns 5 and 6 display tests of the Value decrease Prediction. The dependent variable is natural logarithm of one plus the ratio of the difference between the market value and the book value of assets scaled by the book value of assets, as in Fama and French (1992). The variables of interest are the interaction between *RIVI* and *Excess R&D* or *Excess Innovative Acquisition*. *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Column 5 reports the results for the interaction between *RIVI* and *Excess R&D* and Column 6, the results for the interaction between *RIVI* and *Excess Innovative Acquisition*. Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p -value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

<i>Subject Firms'</i>	R&D	Innovative	R&D	Innovative	Firm Value	
	Intensity	Acquisition	Intensity	Acquisition	5	6
	1	2	3	4		
RIVI	0.006***	0.167***	0.006***	0.166***	0.024	0.048**
	0.001	0.001	0.001	0.002	0.143	0.010
RIVI x Excess R&D					-0.443	
					0.149	
RIVI x Historical R&D					0.193	
					0.396	
RIVI x Excess Innovative Acquisition						-0.023***
						0.002
RIVI x Historical Innovative Acquisition						-0.021**
						0.019
Innovative Acquisition	0.000				0.005*	0.017***
	0.173				0.094	0.003
R&D Intensity		-0.168			1.581***	1.538***
		0.168			0.000	0.000
					0.000	0.000
Control Variables						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²	52930	52930	52930	52930	31279	31279

Table I.A. 3 - Innovation Arms Race – Subsample Analyses

Table I.A. 3 replicates Table 3 tests of the Innovation Arms Race Predictions (see Figure 1) and tests are performed for sub-samples of M&A transactions. In contrast to Table 5 in the paper, the variable of interest is based on the dollar value of transaction. In Panel A, the M&A sample is restricted to change of control transactions. Panel B reports the results when we take into account the innovative acquisitions of public target only and in Panel C, we limit our sample to horizontal transactions. In each panel, Columns 1 and 2 are dedicated to The Correlated Investment Prediction (incentives to innovate). The dependent variables are *R&D Intensity* in column 1, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Column 2, defined as the dollar value of innovative target acquisitions divided by the total value of acquisitions by subject firm. Columns 3 and 4 display tests of the Value decrease Prediction . The dependent variable is natural logarithm of one plus the ratio of the difference between the market value and the book value of assets scaled by the book value of assets, as in Fama and French (1992). The variables of interest are the interaction between *RIVI* and *Excess R&D* or *Excess Innovative Acquisition*. *RIVI* is defined as the dollar value of innovative target acquisitions divided by the total dollar value of acquisitions by rival firms per year (see Equation 1). *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Column 3 reports the results for the interaction between *RIVI* and *Excess R&D* and Column 4, the results for the interaction between *RIVI* and *Excess Innovative Acquisition*. Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

Panel A - Change of Control Transactions

<i>Subject Firms'</i>	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RIVI	0.006***	0.159***	0.022	0.048***
	0.001	0.002	0.236	0.008
RIVI x Excess R&D			-0.334	
			0.295	
RIVI x Historical R&D			0.229	
			0.338	
RIVI x Excess Innovative Acquisition				-0.023***
				0.002
RIVI x Historical Innovative Acquisition				-0.020**
				0.041
Innovative Acquisition	0.000		0.005	0.016***
	0.153		0.129	0.005
R&D Intensity		-0.177	1.545***	1.529***
		0.148	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	51122	51122	30292	30292
Adjusted R ²	0.814	0.152	0.710	0.710

Panel B - Acquisitions of Public Targets Only

<i>Subject Firms'</i>	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4
RIVI	0.003	0.035**	-0.011	0.001
	0.110	0.025	0.551	0.961
RIVI x Excess R&D			-0.930*	
			0.056	
RIVI x Historical R&D			0.131	
			0.497	
RIVI x Excess Innovative Acquisition				0.009
				0.458
RIVI x Historical Innovative Acquisition				-0.004
				0.781
Innovative Acquisition	0.001		-0.005	-0.007
	0.389		0.366	0.209
R&D Intensity		0.052	1.589***	1.551***
		0.395	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	52930	52930	31279	31279
Adjusted R ²	0.813	0.023	0.712	0.711

Panel C - Horizontal Transactions

<i>Subject Firms'</i>	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4
RIVI	0.010***	0.200***	-0.007	0.020
	0.000	0.001	0.704	0.200
RIVI x Excess R&D			-0.360	
			0.199	
RIVI x Historical R&D			0.309	
			0.262	
RIVI x Excess Innovative Acquisition				-0.005
				0.639
RIVI x Historical Innovative Acquisition				0.001
				0.936
Innovative Acquisition	-0.001		0.000	0.004
	0.109		0.981	0.674
R&D Intensity		-0.186	1.592***	1.599***
		0.113	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	36545	36545	22649	22649
Adjusted R ²	0.807	0.169	0.706	0.705

Table I.A. 4 – Innovation Arms Race – Sector Level Results

Table I.A. 5 replicates Table 3 tests of the Innovation Arms Race Predictions (see Figure 1) and tests are performed by sector. In contrast to Table 6 in the paper, the variable of interest is based on the dollar value of transaction. We use the Fama-French 5 industry classification, based on the correspondence table with 4-digit SIC codes provided by the authors. Panel A focuses on the *consumer*, Panel B on the *manufacturing*, Panel C on the *high-tech*, Panel D on the *Healthcare* and Panel E on *Other*. In each panel, Columns 1 and 2 are dedicated to The Correlated Investment Prediction (incentives to innovate). The dependent variables are *R&D Intensity* in column 1, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Column 2, defined as the dollar value of innovative target acquisitions divided by the total value of acquisitions by subject firm. Columns 3 and 4 display tests of the Value decrease Prediction . The dependent variable is natural logarithm of one plus the ratio of the difference between the market value and the book value of assets scaled by the book value of assets, as in Fama and French (1992). The variables of interest are the interaction between *RIVI* and *Excess R&D* or *Excess Innovative Acquisition*. *RIVI* is defined as the dollar value of innovative target acquisitions divided by the total dollar value of acquisitions by rival firms per year (see Equation 1). *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Column 3 reports the results for the interaction between *RIVI* and *Excess R&D* and Column 4, the results for the interaction between *RIVI* and *Excess Innovative Acquisition*. Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

Panel A – Consumer

<i>Subject Firms'</i>	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RIVI	0.000	0.016	0.030	0.010
	0.794	0.500	0.305	0.671
RIVI x Excess R&D			-1.328	
			0.241	
RIVI x Historical R&D			-1.404	
			0.140	
RIVI x Excess Innovative Acquisition				-0.013
				0.517
RIVI x Historical Innovative Acquisition				-0.066
				0.136
Innovative Acquisition	0.000		0.011**	0.014**
	0.710		0.049	0.018
R&D Intensity		-0.168	3.558***	3.238***
		0.716	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	9917	9917	6123	6123
Adjusted R ²	0.786	0.078	0.763	0.762

Panel B - Manufacturing

<i>Subject Firms'</i>	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RIVI	0.000	-0.003	0.000	0.011
	0.685	0.922	0.999	0.491
RIVI x Excess R&D			0.555	
			0.588	
RIVI x Historical R&D			0.427	
			0.328	
RIVI x Excess Innovative Acquisition				0.003
				0.830
RIVI x Historical Innovative Acquisition				0.016
				0.613
Innovative Acquisition	0.000		0.010*	0.010*
	0.448		0.083	0.058
R&D Intensity		0.281	2.770***	2.911***
		0.484	0.001	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	13179	13179	8469	8469
Adjusted R ²	0.789	0.098	0.709	0.709

Panel C - High-Tech

<i>Subject Firms'</i>	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RIVI	0.009***	0.224***	0.006	0.021
	0.001	0.001	0.819	0.308
RIVI x Excess R&D			-0.366	
			0.329	
RIVI x Historical R&D			0.059	
			0.825	
RIVI x Excess Innovative Acquisition				-0.027***
				0.009
RIVI x Historical Innovative Acquisition				-0.021
				0.186
Innovative Acquisition	-0.001		-0.002	0.013**
	0.204		0.579	0.031
R&D Intensity		-0.291	1.044***	1.006***
		0.215	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	15400	15400	8694	8694
Adjusted R ²	0.747	0.174	0.699	0.699

Panel D - Health

<i>Subject Firms'</i>	R&D	Innovative	Firm Value			
	Intensity	Acquisition	1	2	3	4
RIVI	0.007*	0.150**	-0.020	0.020		
	0.076	0.047	0.489	0.422		
RIVI x Excess R&D			-0.497			
			0.326			
RIVI x Historical R&D			0.192			
			0.499			
RIVI x Excess Innovative Acquisition						-0.015
						0.283
RIVI x Historical Innovative Acquisition						-0.033*
						0.068
Innovative Acquisition	-0.001		0.001	0.011		
	0.409		0.780	0.211		
R&D Intensity		-0.240	2.395***	2.319***		
		0.418	0.000	0.000		
Control Variables	Yes	Yes	Yes	Yes		
Year Fixed Effects	Yes	Yes	Yes	Yes		
Firm Fixed Effects	Yes	Yes	Yes	Yes		
Observations	5384	5384	3188	3188		
Adjusted R ²	0.795	0.187	0.686	0.685		

Panel E - Other

<i>Subject Firms'</i>	R&D	Innovative	Firm Value			
	Intensity	Acquisition	1	2	3	4
RIVI	0.003	0.137**	0.127**	0.086*		
	0.148	0.018	0.017	0.086		
RIVI x Excess R&D			0.613			
			0.570			
RIVI x Historical R&D			-1.117*			
			0.062			
RIVI x Excess Innovative Acquisition						-0.038
						0.321
RIVI x Historical Innovative Acquisition						0.037
						0.110
Innovative Acquisition	-0.002**		0.053**	0.066*		
	0.011		0.046	0.070		
R&D Intensity		-0.962**	0.644	0.613		
		0.035	0.364	0.393		
Control Variables	Yes	Yes	Yes	Yes		
Year Fixed Effects	Yes	Yes	Yes	Yes		
Firm Fixed Effects	Yes	Yes	Yes	Yes		
Observations	8610	8610	4620	4620		
Adjusted R ²	0.885	0.068	0.731	0.731		

Table I.A. 5 – Innovation Arms Race – Within-Industry Results

Table I.A. 6 reports the results of the Innovation Arms Race predictions (see Figure 1) depending on the characteristics of industry participants. Panel A reports the results for Leader and Laggard firms and Panel B reports the results for Neck-to-Neck firms. In each panel, Columns 1 and 2 are dedicated to The Correlated Investment Prediction (incentives to innovate). The dependent variables are *R&D Intensity* in column 1, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Column 2, defined as the dollar value of innovative target acquisitions divided by the total value of acquisitions by subject firm. The variables of interest are the interaction between *RIVI* and Leader or Laggard in panel A and the interaction between *RIVI* and *Neck-to-Neck* firms in panel B. *RIVI* is defined as the dollar value of innovative target acquisitions divided by the total dollar value of acquisitions by rival firms per year (see Equation 1). *Leader (Laggard)* is an indicator variable which is equal to 1 if the firm is in the *highest (lowest)* quartile of ROA and market shares. *Neck-to-Neck Firms* is an indicator variable which is equal to 1 if the rival firm is in the highest quartile of the yearly distribution of HP similarity score. In each panel, Columns 3 and 4 display tests of the Value decrease Prediction. The dependent variable is natural logarithm of one plus the ratio of the difference between the market value and the book value of assets scaled by the book value of assets, as in Fama and French (1992). The variables of interest are the interaction between *RIVI and Excess R&D/Excess Innovative Acquisition* and *Leader/Laggard* in Panel A and the interaction between *RIVI and Excess R&D/Excess Innovative Acquisition* and *Neck-to-Neck* firms in Panel B. *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

Panel A – Industry Leaders and Laggards

Subject Firms'	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RIVI			0.025	0.039**
			0.100	0.023
RIVI x Leader	0.005**	0.293***		
	0.010	0.002		
RIVI x Laggard	0.008***	0.083***		
	0.004	0.002		
RIVI x Others	0.003*	0.126***		
	0.074	0.009		
RIVI x Excess R&D x Leader			-2.009***	
			0.005	
RIVI x Excess R&D x Laggard			-0.164	
			0.567	
RIVI x Excess R&D x Others			-0.909*	
			0.069	
RIVI x Excess Innovative Acquisition x Leader				0.000
				0.959
RIVI x Excess Innovative Acquisition x Laggard				-0.020
				0.214
RIVI x Excess Innovative Acquisition x Others				-0.008
				0.387
RIVI x Historical Innovative Acquisition			0.093	
			0.661	
RIVI x Historical R&D				-0.006
				0.546
Innovative Acquisition	0.000		0.000	0.000
	0.117		0.431	0.525
R&D Intensity		-0.190	1.593***	1.508***
		0.110	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	49773	49773	29888	29888
Adjusted R ²	0.83	0.17	0.74	0.74
F-tests				
$\beta_{RIVI \times Leader} - \beta_{RIVI \times Laggard} \neq 0$	-0.003	0.210***		
	0.288	0.008		
$\beta_{RIVI \times Excess R\&D \times Leader} - \beta_{RIVI \times Excess R\&D \times Laggard} \neq 0$			-1.845***	
			0.006	
$\beta_{RIVI \times Excess IA \times Leader} - \beta_{RIVI \times Excess IA \times Laggard} \neq 0$				0.020
				0.266

Panel B – Neck-to-Neck Firms

Subject Firms'	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RIVI			0.022	0.038**
			0.15	0.019
RIVI x Neck-to-Neck	0.013***	0.276***		
	0.008	0.000		
RIVI x Others	0.003***	0.137***		
	0.007	0.005		
RIVI x Excess R&D x Neck-to-Neck			-0.467	
			0.195	
RIVI x Excess R&D x Others			-0.760*	
			0.052	
RIVI x Excess Innovative Acquisition x Neck-to-Neck				-0.004
				0.358
RIVI x Excess Innovative Acquisition x Others				-0.003
				0.620
RIVI x Historical Innovative Acquisition			0.159	
			0.478	
RIVI x Historical R&D				-0.006
				0.52
Innovative Acquisition	-0.001*		0.000	0.000
	0.087		0.418	0.706
R&D Intensity		-0.208*	1.599***	1.512***
		0.083	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	59568	59568	35175	35175
Adjusted R ²	0.839	0.261	0.712	0.712
F-tests				
$\beta_{RIVI \times Neck-to-Neck} - \beta_{RIVI \times Others} \neq 0$	0.010**	0.139**		
	0.033	0.018		
$\beta_{RIVI \times Excess R\&D Neck-to-Neck} - \beta_{RIVI \times Excess R\&D Others} \neq 0$			0.293	
			0.476	
$\beta_{RIVI \times Excess IA \times Neck-to-Neck} - \beta_{RIVI \times Excess IA \times Others} \neq 0$				-0.001
				0.906

Table I.A. 6 - M&A and Rivals' Incentives to Innovate – Instrumental Variable Estimates

Table I.A. 8 replicates Table 3 tests of the Innovation Arms Race Correlated Investment using an instrumental variable approach. The dependent variables are *R&D Intensity* in column 2, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Column 4, defined as the number of innovative target acquisitions divided by the number of acquisitions by subject firm. The variable of interest is *RIVI*, defined as the dollar value of innovative target acquisitions divided by the total dollar value of acquisitions by rival firms per year (see Equation 1) and is instrumented by *Rival's Tax Induced R&D* (it is the predicted value of firm-level investment in R&D due to tax credit incentives and is obtained by from the Hall-Jorgenson user cost of R&D and replicating the procedure described in Bloom et al. (2013) Internet Appendix B.3.1). Columns 1 and 3 report the results obtained from first stage regression and Columns 1 and 4 display the results from second stage regression. Estimates are obtained using 2SLS regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

	1st Stage		2nd Stage	
	RIVI	R&D Intensity	RIVI	Innovative Acquisition
	1	2		2
Rival's Tax Induced R&D	-0.028*** 0.000		-0.029*** 0.000	
RIVI		0.097** 0.043		2.345** 0.028
Innovative Acquisition	0.020*** 0.000	-0.003** 0.016		
R&D Intensity			0.224*** 0.000	-0.755** 0.013
Tax Induced R&D	-0.027*** 0.000	0.016*** 0.000	-0.030*** 0.000	-0.007 0.120
Joint test of excluded instruments F(9,6860)	43.21		36.86	
Prob >F	0.000		0.000	
Control Variables	Yes	Yes		Yes
Year Fixed Effects	Yes	Yes		Yes
Firm Fixed Effects	Yes	Yes		Yes
Observations	41660	41660	41660	41660
Overall R ²		0.346		0.041
Chi ²		651.67		135.36

Table I.A. 7 - M&A and Rivals' Incentives to Innovate – Innovation Efficiency

Table I.A. 7 reports the effects of Innovation Arms Race on innovation efficiency. The dependent variables are *Number of Patents* in Columns 1 and 2 of panel A, defined as log of one plus number of patents, and *Number of Citations* in Columns 1 and 2 of panel B, defined as log of one plus number of citations. In both the panels, the variables of interest are the interaction between *RIVI* and *Excess R&D* or *Excess Innovative Acquisition*. *RIVI* is defined as the dollar value of innovative target acquisitions divided by the total dollar value of acquisitions by rival firms per year (see Equation 1). *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Column 1 reports the results for the interaction between *RIVI* and *Excess R&D* and Column 2, the results for the interaction between *RIVI* and *Excess Innovative Acquisition*. Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

Panel A – Patents based

<i>Subject Firms'</i>	Number of Patents	
	1	2
RIVI	-0.025	0.007
	0.251	0.701
RIVI x Excess R&D	0.431*	
	0.070	
RIVI x Historical R&D	0.321	
	0.119	
RIVI x Excess Innovative Acquisition		-0.008
		0.195
RIVI x Historical Innovative Acquisition		-0.004
		0.697
Innovative Acquisition	0.001	0.006
	0.701	0.152
R&D Intensity	-0.171	0.046
	0.282	0.746
Control Variables	Yes	Yes
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	3772	3772
Adjusted R ²	0.92	0.92

Panel B – Citation based

<i>Subject Firms'</i>	Number of Citations	
	1	2
RIVI	-0.031	-0.012
	0.254	0.671
RIVI x Excess R&D	-0.090	
	0.738	
RIVI x Historical R&D	0.217	
	0.206	
RIVI x Excess Innovative Acquisition		0.024**
		0.031
RIVI x Historical Innovative Acquisition		0.013
		0.234
Innovative Acquisition	-0.006*	-0.019**
	0.091	0.016
R&D Intensity	0.396*	0.385*
	0.088	0.060
Control Variables	Yes	Yes
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	5771	5771
Adjusted R ²	0.76	0.76

Table I.A. 8 - Innovation Arms Race – Extensive Margin Analyses

Table I.A. 3 displays results of Innovation Arms Race Predictions (see Figure 1) and tests are performed at the intensive margin (the sample of firms include firms that are not subject to rival innovative acquisition pressure). In contrast to Table 9 in the paper, the variable of interest is based on the dollar value of transaction. Columns 1 and 2 are dedicated to The Correlated Investment Prediction (incentives to innovate). The dependent variables are *R&D Intensity* in column 1, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Column 2, defined as the dollar value of innovative target acquisitions divided by the total value of acquisitions by subject firm. The variable of interest is *RIVI*, defined as the dollar value of innovative target acquisitions divided by the total dollar value of acquisitions by rival firms per year (see Equation 1). Columns 3 and 4 display tests of the Value decrease Prediction. The dependent variable is natural logarithm of one plus the ratio of the difference between the market value and the book value of assets scaled by the book value of assets, as in Fama and French (1992). The variables of interest are the interaction between *RICI* and *Excess R&D* or *Excess Innovative Acquisition*. *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Column 3 reports the results for the interaction between *RIVI* and *Excess R&D* and Column 4, the results for the interaction between *RIVI* and *Excess Innovative Acquisition*. Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

<i>Subject Firms'</i>	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RIVI	0.003*	0.157***	0.021*	0.036**
	0.052	0.001	0.100	0.017
RIVI x Excess R&D			-0.531**	
			0.044	
RIVI x Historical R&D			0.082	
			0.634	
RIVI x Excess Innovative Acquisition				-0.030***
				0.000
RIVI x Historical Innovative Acquisition				-0.025***
				0.005
Innovative Acquisition	-0.001*		0.006**	0.020***
	0.080		0.039	0.000
R&D Intensity		-0.140*	1.376***	1.305***
		0.077	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	81375	81375	47011	47011
Adjusted R ²	0.818	0.160	0.709	0.709

Table I.A. 9 - Innovation Arms Race – Industry x Year Fixed Effects

Table I.A. 10 replicates Table 3 tests of the Innovation Arms Race Predictions (see Figure 1). In contrast to Table 3 in the paper, we enhance our econometric specification by adding Industry x Year Fixed Effects. Industry is defined at Standard Industry Classification (SIC) 3 level. Panel A reports the results when the variable of interest is based on the number of transactions and Panel A reports the results when the variable of interest is based on the dollar value of transaction. Columns 1 and 2 are dedicated to The Correlated Investment Prediction (incentives to innovate). The dependent variables are *R&D Intensity* in column 1, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Column 2, defined as the number of innovative target acquisitions divided by the number of acquisitions by subject firm. Columns 3 and 4 display tests of the Value decrease Prediction. The dependent variable is natural logarithm of one plus the ratio of the difference between the market value and the book value of assets scaled by the book value of assets, as in Fama and French (1992). The variables of interest are the interaction between RICI or RIVI and *Excess R&D* or *Excess Innovative Acquisition*. RICI is defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (see Equation 1). RIVI is defined as the dollar value of innovative target acquisitions divided by the total dollar value of acquisitions by rival firms per year (see Equation 1). *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Column 3 reports the results for the interaction between RICI or RIVI and *Excess R&D* and Column 4, the results for the interaction between RICI or RIVI and *Excess Innovative Acquisition*. Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

Panel A – Numbers based

<i>Subject Firms'</i>	R&D	Innovative	Firm Value	
	Intensity	Acquisition	3	4
	1	2		
RIVI	0.005***	0.036***	0.003	0.016
	0.000	0.001	0.886	0.270
RIVI x Excess R&D			-0.555*	
			0.057	
RIVI x Historical R&D			0.082	
			0.732	
RIVI x Excess Innovative Acquisition				-0.032***
				0.005
RIVI x Historical Innovative Acquisition				-0.031
				0.119
Innovative Acquisition	-0.002**		0.019**	0.035***
	0.042		0.019	0.001
R&D Intensity		-0.165**	1.672***	1.576***
		0.018	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
IndusYear Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	57699	57699	33754	33754
Adjusted R ²	0.810	0.184	0.737	0.737

Panel B – Value based

<i>Subject Firms'</i>	R&D	Innovative	Market Value	
	Intensity	Acquisition	5	6
	1	2		
RIVI	0.004***	0.060**	0.001	0.019**
	0.002	0.026	0.941	0.020
RIVI x Excess R&D			-0.427	
			0.171	
RIVI x Historical R&D			0.142	
			0.459	
RIVI x Excess Innovative Acquisition				-0.017**
				0.022
RIVI x Historical Innovative Acquisition				-0.017*
				0.061
Innovative Acquisition	-0.001***		0.004	0.013**
	0.009		0.194	0.017
R&D Intensity		-0.386***	1.639***	1.582***
		0.008	0.000	0.000
<i>Control Variables</i>	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	51025	51025	29855	29855
Adjusted R ²	0.806	0.141	0.737	0.737

Table I.A. 10 - Innovation Arms Race – Alternative definition of variable of interest

Table I.A. 11 replicates Table 3 tests of the Innovation Arms Race Predictions (see Figure 1). In contrast to Table 3 in the paper, we alternatively define the variable of interest. Columns 1 and 2 are dedicated to The Correlated Investment Prediction (incentives to innovate). The dependent variables are *R&D Intensity* in column 1, defined as R&D expenses divided by total assets and *Innovative Acquisition* in Column 2, defined as the dollar value of innovative target acquisitions divided by the total dollar value of acquisitions by subject firm. Columns 3 and 4 display tests of the Value decrease Prediction . The dependent variable is natural logarithm of one plus the ratio of the difference between the market value and the book value of assets scaled by the book value of assets, as in Fama and French (1992). The variables of interest are RIAT and the interaction between *RIAT* and *Excess R&D* or *Excess Innovative Acquisition*. *RIAT* is defined as the dollar value of innovative target acquisitions divided by the total assets by rival firms per year. *Excess R&D* is defined as the difference between *R&D Intensity* of the subject firm and its historical *R&D Intensity* (the average *R&D Intensity* over the last three years), and *Excess Innovative Acquisition* is the difference between *Innovative Acquisition* of the subject firm and its historical *Innovative Acquisition* (the average *Innovative Acquisition* over the last three years). Column 3 reports the results for the interaction between *RIAT* and *Excess R&D* and Column 4, the results for the interaction between *RIAT* and *Excess Innovative Acquisition*. Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

<i>Subject Firms'</i>	R&D	Innovative	Market Value	
	Intensity	Acquisition	5	6
	1	2		
RIAT	0.014*	0.931***	0.223**	0.430**
	0.088	0.001	0.041	0.011
RIAT x Excess R&D			-3.419**	
			0.012	
RIAT x Historical R&D			1.780*	
			0.089	
RIAT x Excess Innovative Acquisition				-0.071**
				0.039
RIAT x Historical Innovative Acquisition				-0.082**
				0.030
Innovative Acquisition	0.000		0.004	0.011**
	0.234		0.208	0.034
R&D Intensity		-0.145	1.577***	1.525***
		0.231	0.000	0.000
<i>Control Variables</i>	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	52969	52969	31306	31306
Adjusted R ²	0.813	0.161	0.714	0.713

Table I.A. 11 - Innovation Arms Race – Multiple Imputation Analyses

Table I.A. 12 tests The Correlated Investment Prediction (incentives to innovate) using multiple imputation analysis. The dependent variables are *R&D Intensity*, defined as R&D expenses divided by total assets. The variables of interest are RICI and RIVI. *RICI* is defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (see Equation 1). *RIVI* is defined as the dollar value of innovative target acquisitions divided by the total dollar value of acquisitions by rival firms per year (see Equation 1). Estimates are obtained using a fixed-effect regression model. Standard errors are clustered at the firm level (p-value is reported below the coefficient estimate). The inclusion of fixed effects and control variables are indicated in the last rows of the table. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

<i>Subject Firms'</i>	R&D Intensity	
	1	2
RICI	0.008***	
	0.000	
RIVI		0.006***
		0.000
<i>Control Variables</i>	Yes	Yes
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	55413	45842
Adjusted R ²	0.816	0.816