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-tech sector. Markov-switching regression based identification of arms race periods at the industry level brings additional insights into industry features conducive to innovation arms races. Patents and patent citations-based evidence shows no sign of innovation investment efficiency decline, suggesting that innovation arms races generate a transfer of economic rents to consumers. Additionally, cumulative abnormal returns and offer premium analyses indicate that target shareholders benefit from this increased competition between acquirers.

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"*
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> *(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 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 *responsive investments* prediction) and (ii) the resulting outcome will be value destroying for the parties in competition, consistent with either a decline in 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)

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

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 hypotheses' 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 responsive investment prediction), representing a hefty 85% offer premium. Being unable to catch up with Google in the online search race, Microsoft finally announced a $6.2 billion write-down 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 on 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 Reuter (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 responsive 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 rivals[2]. 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 acquisition intensity by the ten closest rivals in the product market space (rivals' IA henceforth). To test the Arms Race Hypothesis responsive investment prediction, we regress the firm's R&D (the R&D equation) and IA intensity (the IA equation) on this measure of rivals' innovative acquisitions. Testing the second Arms Race Hypothesis prediction (the value decrease prediction) entails studying the value effect of these investments. We do so by

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

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 (lnMTBA) on firm excess investments (defined as the difference between the current year investment and the three-year historical average) in R&D and innovative acquisitions in response to rivals' innovative acquisitions. This test assumes that investors have not (fully) anticipated the start of an arms race process before it starts, 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.

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 (lnMTBA). 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 and time-varying control variables to the test of the responsive 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 the focal firm's R&D by 5% and IA by 42% 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 innovative acquisitions), 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 responsive investment prediction. This emphasizes the importance of taking into account small private targets to capture rivals' innovative acquisitions effects.

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 responsive 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 rivals' innovative acquisitions 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 responsive investment prediction test with two instrumental variable approaches and three placebo tests. 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. Alternatively, keeping only rival firms located outside the focal firm commuting zone, we use the intensity of R&D investment in rivals' commuting zone as an instrument for rivals' R&D investment. Placebo tests are implemented using sales and general administrative expenses, cost of goods sold and working capital-based dependent variables in place of R&D and IA. Results obtained using our instrument and a two-stage least square estimator (2SLS) confirm that a causal interpretation of the responsive investment prediction results is warranted. Moreover, the placebo tests are insignificant, providing evidence against broader peer effects.

Market value regressions that test the arms race's value decrease prediction display negative and statistically significant coefficients for the interaction terms between rival innovative acquisitions and firm excess R&D and excess innovative acquisitions[3]. 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 responsive investment prediction test but remain sizeable, with a value loss of 10% under the combined effect of a one standard deviation increase of rival IA (count based) and excess R&D or excess innovative acquisitions.

Results obtained so far prove moreover to be robust to many alternative specifications, in particular the addition of industry × 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 innovative acquisitions 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 classification[4]. 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. To further examine industry level differences, we classify industries by the level of pre-existing economic rent (using the return on assets (ROA) as proxy for the Lerner (1934) index). The empirical support of the arms race responsive investment prediction

[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.

is particularly strong in low pre-existing rent industries, consistent with firms active in more competitive industries being more reactive to rival investments in innovation.

To gain more insights industry level characteristics conducive to innovation arms races between industry participants, we adopt Markov-switching regressions. This allows us to identify, at the industry level, arms race periods. We then investigate whether competition, barriers to entry, innovation intensity and resource reallocations through M&A transactions impact the emergence of arms races. Results confirm that innovation intensive industries are more prone to arms races. In addition, intensive resource reallocations through M&A activity, higher profitability and firm size increase the probability of an innovation arms race, while industries featuring more similar products appear less exposed to this form of competition.

In addition, we 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 Kogan et al. (2017) dataset[5] 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.

We finally assess whether the 2007 Google-Microsoft fight to acquirer DoubleClick was an isolated case or, on the contrary, representative of the competitive process among rivals to acquirer innovative targets. To this end, we report the results of cross-sectional regressions that relate acquirer, target and M&A transaction cumulative abnormal returns (CAR) as well as the offer premium to rival innovative acquisitions, in addition to a set of control variables classically used in previous studies. Our results indicate that the Google-Microsoft case is far from an atypical case: rival innovative acquisitions (lagged by one year with respect to the M&A transaction announcement year) are negatively correlated with acquirer and M&A transaction CAR's but positively correlated with target CAR's and the offer premiums. Target shareholders clearly benefit from rival innovative acquisitions induced transactions. These results are also consistent with the Arms Race Hypothesis value decrease prediction: to face rival competition, acquirers are willing to give up more value to innovative targets to acquirer them.

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 that the actual effect of any given M&A transaction on acquirer rivals' incentives to innovate is context dependent.

[5] Available at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.

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 (e.g. 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 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 *laisse-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 mis-valuation 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 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 granular data on product and patent characteristics, the authors uncover strategies designed by incumbent firms to kill potentially threatening innovations: incumbents acquire rivals in their early life cycle stage and stop 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 (responsive 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 Center for Research in Security Prices (CRSP 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 dataset[6] that starts in 1989 and ends in 2019 and the requirement of three years of historical data to compute excess R&D and excess innovative acquisitions (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 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

[6] Available at http://hobergphillips.tuck.dartmouth.edu/industryclass.htm.

acquisitions), it appears that, on average, acquirers undertake approximately two acquisitions per year.

3.2. Variables

Dependent Variable

To test the arms race responsive 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, innovative acquisitions, defined as the number of innovative target acquisitions divided by the number of acquisitions[7]. 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 innovative acquisitions identification procedure (industries are classified as innovative if they rank in the highest quartile by R&D intensity). The percentage of innovative acquisitions 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 innovative acquisitions (Column 4) to the subset of 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

[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.

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 lnMTBA. 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. Using a market valuation-based measure to test the arms race value decrease prediction entails implicit assumptions on the investors' information set. Specifically, the predicted market reaction depends on whether one assumes that investors know that the subject firm is involved in an arms race once the rivals make their acquisitions or whether the subject firm's response reveals that the arms race is happening. It is in the latter case that we would predict a negative market response to the subject firm's actions.

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 Arms Race Hypothesis responsive investment prediction, Panel B the value decrease prediction, Panel C, to variables used in CAR cross-sectional regression analyses and Panel D, to variables used in placebo tests. Variables are grouped into dependent, independent and control variables. In our sample of 59,568 firm-year observations (Panel A), 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 innovative acquisitions by firm-year, which is 0.091. The distribution is again highly right skewed, as the third quartile is still 0. Innovative acquisitions are in fact concentrated into the last decile of the distribution (untabulated). In Panel B, on a reduced sample of 35,204 firm-year observations due to data availability constraints, 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. Panel C pertains to variables used in cross-sectional regression analyses of CAR's. The number of observations is limited to the number of M&A transactions with data. Average acquirer, target and combined 5-day centered CAR, respectively 0.6%, 26.5% and 1.9%, are in-line with figures reported in previous contributions dealing with a large sample of M&A transactions (e.g., Betton et al., 2008). This is also the case of the average offer premium (48.65%). Finally, in Panel D, we report descriptive statistics for alternative dependent variables used in placebo tests (sales and general administrative expenses divided by total sales - denoted SG&A, cost of goods sold divided by total sales – denoted COGS and working capital divided total sales – denoted WC).

Independent Variables

To test the arms race responsive investment prediction, we are interested in the effect of rival innovative acquisitions on the focal 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 Based[8] 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 $10NN$).
- 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 innovative acquisitions by $10NN$ rivals in year t: $RIAC_{it} = \sum_{j\in 10NN_{it}} IAC_{ijt}$ where IAC_{ijt} is the number of innovative acquisitions 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}:

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

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

[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.

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 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 acquisitions by $10NN$ rivals are innovative, with a highly right skewed distribution, more than half of the sample undertaking no innovative acquisitions (the median is 0). The skewness reflects the fact that innovative acquisitions cluster, consistently with the Arms Race Hypothesis.

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 innovative acquisitions 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 innovative acquisitions into the three-year historical R&D and innovative acquisition averages and the current excess R&D and innovative acquisitions. This procedure generates the historical and excess R&D intensity and innovative acquisitions interactions with RICI, our two independent variables of interest to test the value decrease prediction:

$$RICI_{it} \times R\&D_{it}^{histo} = RICI_{it} \times (\tfrac{1}{3}\sum_{\tau=1}^{3} R\&D_{it-\tau}) \tag{2}$$

$$RICI_{it} \times IA_{it}^{histo} = RICI_{it} \times (\tfrac{1}{3}\sum_{\tau=1}^{3} IA_{it-\tau}) \tag{3}$$

$$RICI_{it} \times R\&D_{it}^{excess} = RICI_{it} \times (R\&D_{it} - \tfrac{1}{3}\sum_{\tau=1}^{3} R\&D_{it-\tau}) \tag{4}$$

$$RICI_{it} \times IA_{it}^{excess} = RICI_{it} \times (IA_{it} - \tfrac{1}{3}\sum_{\tau=1}^{3} IA_{it-\tau}) \tag{5}$$

where $R\&D_{it}^{excess}$ is the firm i excess R&D intensity in year t, IA_{it}^{excess}, the excess innovative acquisitions 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

Decree[9] on investment. 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 innovative acquisitions, with all three first 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 responsive 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). The ratios are winsorized at 1st and 99th percentile. 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 (Chang 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

[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. Frattoroli (2020) shows that the adoption of this new legislation has significantly reduced the probability of being acquired for firms active in these industries.

to endogeneity, we also use a measure of firm level R&D user cost 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} by the authors. 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 responsive investment prediction (firm size, ROA, leverage, liquidity, intangible ratio) does not alter our results (untabulated).

3.3. Econometric Specification

The Responsive 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:

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

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

where $R\&D_{it}$ and $IA_{i,t}$ are our dependent variables and stand for R&D intensity and innovative acquisitions, 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 (see Equation 1), $\boldsymbol{Controls'}_{\boldsymbol{i,t-1}}$ 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 responsive investment prediction of the Arms Race Hypothesis, we expect that γ to be positive in Equations 6 and 7.

Keeping in mind that the variable of interest is RICI, the presence of $IA_{i,t}$ at the right-hand side of Equation 6 and $R\&D_{it}$ 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 RICI itself, our independent variable for which a causal interpretation is relevant, to the robustness check Section 5.1. We also report results without $R\&D_{it}$and $IA_{i,t}$as right-hand side variables to check whether our results are affectede 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:

$$lnMTBA_{it} = \alpha_i + \beta_t + \gamma\, RICI_{it} + \delta\, R\&D_{it} + \tau\,(RICI_{it} \times R\&D_{it}^{excess}) + \theta\,\left(RICI_{it} \times R\&D_{it}^{histo}\right) + \mu\, IA_{it} + \boldsymbol{Controls'_{it}}\,\boldsymbol{\nu} + \epsilon_{it} \qquad (8)$$

$$lnMTBA_{it} = \alpha_i + \beta_t + \gamma\, RICI_{it} + \delta\, IA_{it} + \tau\,(RICI_{it} \times IA_{it}^{excess}) + \theta\,\left(RICI_{it} \times IA_{it}^{histo}\right) + \mu\, R\&D_{it} + \boldsymbol{Controls'_{it}}\,\boldsymbol{\nu} + \eta_{it} \qquad (9)$$

where $\boldsymbol{Controls}$ 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. As noted in Section 3.2, this specification assumes that the start of an arms race process has not been fully anticipated by investors as soon as rivals undertake innovative acquisitions. Under the value decrease prediction, 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'

[10] Coefficients of $IA_{i,t}$ and $R\&D_{it}$can however not be given any causal interpretation as the rank and order conditions for identification are not met.

[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 lnMTBA 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).

anticipations around rival innovative acquisition announcement in Appendix 2. Results are consistent with our assumption of no (or limited) arms race anticipations.

As emphasized in Figure 1, it is the combination of positive γ in Equations 6 and 7 (responsive 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 innovative acquisitions 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 responsive investment prediction: lagged innovative acquisitions by rivals drives firms to invest more in R&D and innovative acquisitions. Moreover, these effects are economically sizable: a one standard deviation increase in RICI increases R&D by 5 % and innovative acquisitions by 42 % 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 innovative acquisitions is negative and significant at the 1% confidence level, in support of the value decrease prediction. The economic effects are smaller than for the responsive investment prediction but yet sizeable: a one standard deviation increase in rival innovative acquisitions (count based) combined with a one standard deviation increase in firm excess R&D leads to a lnMTBA decline of 10%. A similar result is observed in the case of one standard deviation increase in firm excess innovative acquisition. The combination of Columns 1 to 4 results (responsive 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. Given that innovation contributes to economic growth, one policy implication of these findings is that, in the aggregate, the M&A market contributes to foster economic growth through innovation.

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 innovative acquisitions 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 responsive 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 innovative acquisitions 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): all coefficients of interest keep their statistical significance but statistical significance weakens. Point estimates are significantly smaller in Columns 1 and 2 (the responsive investment prediction tests). 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 does not affect our results, except that in Column 4, the coefficient of the interaction term between RICI and excess innovative acquisitions losing its statistical significance (but keeping 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 rival innovative acquisitions on the firm incentives to invest in innovation is confirmed for transactions specifically subject to stricter regulation. One must however be aware the this can be a manifestation of the regulation deterrence effect and not evidence that regulation is in itself needless.

4.2. The Arms Race Hypothesis – Industry Level Analyses

Average results mask potentially significant industry heterogeneity, even if our inclusion of firm fixed-effects should absorb a large part of it[12]. This motivates us to conduct industry level analyses next. To shed some light on potential industry heterogeneity, we select the Fama and French five industries classification[13]. Fama and French provide a matching table that allows us to group SIC codes

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

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

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 Panels A and B report our results. Panel A is dedicated to the responsive investment prediction and Panel B to the value decrease one. In Panel A, Columns 1 to 5 report, for each Fama and French industry, results corresponding to Table 3 Column 1 (R&D Intensity), and Columns 6 to 10 report results corresponding to Table 3 Column 2 (Innovative Acquisition). In Panel B, we report results corresponding to Table 3 Columns 5 and 6 by Fama and French industry (Columns 1 and 2 for Consumer, Columns 3 and 4 for Manufacturing, Columns 5 and 6 for High-Technology, Columns 7 and 8 for Healthcare and Columns 9 and 10 for Others). The Arms Race Hypothesis predictions find no support in the consumer and manufacturing industries. In contrast, results for the high-technology industry bring support to both the responsive investment and the value decrease predictions (except for the coefficient of the interaction terms between RICI and excess R&D in Panel B Column 5, which is negative but not statistically significant), despite drastically smaller samples (16,600 and 9,357 firm-year observations for the responsive investment prediction and the value decrease predictions respectively). For the healthcare industry, we find support for the Arms Race Hypothesis predictions with respect to R&D, but not for innovative acquisitions. Finally, for the Others industry, coefficients are mostly not significant, perhaps because this sub-sample aggregates firms from too heterogenous competitive environment. While we cannot exclude the possibility that part of these conclusions are due to a lack of power to reject the null hypothesis (sample sizes are drastically reduced), our industry level results are intuitive: innovation is certainly a powerful driver of competition in the high-technology and, to some extent, in the health-care industries and therefore, these offer conditions favorable to the emergence of innovation arms races between competitors.

Schumpeter (1943) emphasizes the importance of the firm's competitive environment to understand innovation choices in response to competition shocks and posits the rent dissipation hypothesis. As an initial exploration of this intuition, we next study whether firm reaction to rival innovative acquisitions depends on the pre-existing industry rents as characterization of industry competition. In the spirit of the Lerner index (Lerner, 1934), we use the 3-digit SIC industry average return on assets (ROA), computed using Compustat firms, to proxy for existing industry rents. We then rank industries by average ROA and define HighRent and LowRent dummy variables that take the value of one when the corresponding industry is in the highest or lowest quartile of average ROA industry distribution (industries in the second and third quartile are identified by the BaseRent dummy variable). One year lagged values of HighRent, LowRent and BaseRent dummy variables are then interacted with the $RICI_{it-1}$ term present in Equations 6 and 7 and with the $(RICI_{it} \times R\&D_{it}^{excess})$ and $(RICI_{it} \times IA_{it}^{excess})$ terms present in Equations 8 and 9 respectively. This allows us to condition the effect of these terms on pre-existing industry rents and leads to the following regression specifications:

$$R\&D_{it} = \alpha_i + \beta_t + \gamma_0 \, (HighRent_{it-1} \times RICI_{it-1}) + \gamma_1 \, (LowRent_{it-1} \times RICI_{it-1}) + \gamma_2 \, (BaseRent_{it-1} \times RICI_{it-1}) + \delta \, IA_{it} + \boldsymbol{Controls'_{it-1}} \, \boldsymbol{\omega} + \epsilon_{it} \quad (10)$$

$$IA_{it} = \alpha_i + \beta_t + \gamma_0 \, (HighRent_{it-1} \times RICI_{it-1}) + \gamma_1 \, (LowRent_{it-1} \times RICI_{it-1}) + \gamma_2 \left(BaseRent_{it-1} \times RICI_{,t-1}\right) + \delta \, R\&D_{,t} + \boldsymbol{Controls'_{it-1}} \, \boldsymbol{\omega} + \eta_{it} \quad (11)$$

$$lnMTBA_{it} = \alpha_i + \beta_t + \gamma \, RICI_{it} + \delta \, R\&D_{it} + \tau_1 \, (RICI_{it} \times R\&D_{it}^{excess} \times HighRent_{it-1}) + \tau_2 \, (RICI_{it} \times R\&D_{it}^{excess} \times LowRent_{it-1}) + \tau_3 \, (RICI_{it} \times R\&D_{it}^{excess} \times BaseRent_{it-1}) + \theta \left(RICI_{it} \times R\&D_{it}^{histo}\right) + \mu \, IA_{it} + \boldsymbol{Controls'_{it}} \, \boldsymbol{\nu} + \epsilon_{it} \quad (12)$$

$$lnMTBA_{it} = \alpha_i + \beta_t + \gamma \, RICI_{it} + \delta \, IA_{it} + \tau_1 \, (RICI_{it} \times IA_{it}^{excess} \times HighRent_{it-1}) + \tau_2 \, (RICI_{it} \times IA_{it}^{excess} \times LowRent_{it-1}) + \tau_3 \, (RICI_{it} \times IA_{it}^{excess} \times BaseRent_{it-1}) + \theta \left(RICI_{it} \times IA_{it}^{histo}\right) + \mu \, R\&D_{it} + \boldsymbol{Controls'_{it}} \, \boldsymbol{\nu} + \eta_{it} \quad (13)$$

where notations are the same as in Equations 6 to 9.

Results are reported in Table 5 Panel C. Responses to rival innovative acquisitions are driven by low pre-existing rent industries, as indicated by the high point estimate and statistical significance of $(LowRent_{it-1} \times RICI_{it-1})$ interaction term coefficients in Columns 1 and 2. This evidence is consistent with more competitive industries (low pre-existing rent industries) being more responsive to innovation driven competitive shocks (rival innovative acquisitions). With respect to the value decrease prediction, the negative effect of excess R&D is concentrated in high pre-existing rent industries while the negative effect of excess innovative acquisition appears stronger in low pre-existing rent industries. These results suggest that the value effects of increase in R&D and innovative acquisitions with respect to historical levels are sensitive to the level of existing competition within the industry, perhaps because the investment horizons of R&D and innovation acquisitions are significantly different.

4.3. The Arms Race Hypothesis – Industry Characteristics

Arms Race Processes Identification

Section 4.2 results indicate that some industries are more prone to witness innovation arms races. However, this doesn't mean that these industries are permanently in such state—one can expect that incentives to engage into arms races are a time-varying. To study industry level characteristics that create an environment conducive to such form of competition among firms, we need therefore to identify, at the industry level, periods of innovation arms races. To this end, we adopt a Markov-switching regressions-based approach.

Markov-switching regressions assume the existence of a given number of unobserved states that govern regression parameters. Modelling the transition between these unobserved states as a Markov chain, Markov-switching regressions provide estimates of the probability to transition from one state to the another, the time-varying probabilities to be in a given state and the regression parameters in each state, all estimates of prime interest for us.

The first modelling decisions that we face are the selection of an industry classification, that drives the granularity of the analysis, and the choice of the number of unobserved states, that determines the number of parameters of the Market-switching regressions that are to be estimated at the industry level. Our empirical setup is highly constrained. We study NYSE, NASDAQ and AMEX Compustat-CRSP firms (excluding financial institutions) from 1996 to 2019, yielding an average of around 5,000 firms per year over our 24-year sample. The choice of an industry classification is a trade-off between enough industries to have significant cross-sectional variation and enough firms by industry to have representative samples that average out firm level idiosyncrasies. We select the 2-digit SIC industry classification, keeping only industries with at least 10 firms in each and every year. Being limited to 24 yearly observations by industry, we fix the number of unobservable states to two, in order the reduce as much as possible the number of estimated parameters, while still benefiting from the Markov-switching regression approach to capture change of regimes.

The second modeling decision pertains to the regression framework that allows us to identify arms races (Equations 6 and 7 for the responsive investment prediction and Equations 8 and 9 for the value decrease prediction). These regression equations focus on two dimensions of investments in innovation: R&D and innovative acquisitions. Working at the 2-digit SIC industry level, the number of innovative acquisitions by industry-year is limited (Table 2 descriptive statistics indicate that the third quartile of the innovative acquisitions distribution in our 59,658 firm-year sample is still zero). We therefore limit our attention to investments in R&D (Equations 6 and 8), with the additional benefit of significantly reducing the number of parameters to be estimated by industry.

This empirical design is restrictive and calls for caution so that the results that we report in this Section must be considered as exploratory. Under these restrictions, we estimate, for each 2-digit SIC industries, the following two state time-series Markov-switching regressions:

$$R\&D_t^{Ind} = \alpha_s + \beta_s\, RICI_{t-1}^{Ind} + \epsilon_t^{Ind} \tag{14}$$

$$lnMTBA_t^{Ind} = \alpha_s + \beta\, RICI_t^{Ind} + \gamma\, R\&D_t^{Ind} + \delta_s\, (RICI_t^{Ind} \times R\&D_t^{excess,Ind}) + \epsilon_t^{Ind} \tag{15}$$

where Ind is for industry, t is for year, s is for state ($high$ or low), $R\&D_t^{Ind}$, $RICI_t^{Ind}$, $lnMTBA_t^{Ind}$ and $R\&D_t^{excess,Ind}$ are equally-weighted 2-digit SIC industry averages corresponding to $R\&D_{it}$, $RICI_{it}$, $lnMTBA_{it}$ and $R\&D_{it}^{excess}$ in Equations 6 and 8. Note that we include no control variables. This is again motivated by the limited number of observations at our disposal for any given industry (24 years) that constrains the number of parameters that can be estimated. However, the use of industry average values for $R\&D_{it}$, $RICI_{it}$, $lnMTBA_{it}$ and $R\&D_{it}^{excess}$ should help to mitigate the influence of firm specific characteristics.

We are interested in estimates of β_s and δ_s. These parameters, used in conjunction with estimated time-varying probabilities of being in $high$ and low states, will allow us to identify periods of innovation arms race in a given industry. More specifically, we identify a period of innovation arms race if the probability of high responsive investment is above 0.5, the probability of a low value regime is above 0.5, β_{high} is strictly positive and δ_{low} is strictly negative, consistently with specifications in Equations 6 and 8.

The combination of the two Markov-switching regression models specified in Equations 14 and 15 and this empirical definition of innovation arms races allows us identify 26 2-digit SIC industries with at least one arms race period. We report the results obtained for these industries in Figure 2 for 24 industries[14]. Each graphic is for one given 2-digit SIC industry (the industry code is provided in title). The time (in years) is reported on the horizontal axis and the corresponding probabilities to be in a $high$ Markov regime are reported on the vertical axis. The blue line pertains to the responsive investment prediction (Equation 14) and the red line to the value decrease prediction (Equation 15). Shaded areas are identified periods of innovation arms races. Several interesting patterns emerge. The Markov-switching regressions capture clear jumps in probabilities to be in high responsive investment and value decrease states, that allow unambiguous identification of innovation arms race periods. The number of such arms race periods and their persistence vary significantly from industry to industry, ranging from one highly persistent period in 2-digit SIC industry 23 (apparel and other

[14] We drop 2-digit SIC industries 83 (Social Services) and 87 (Engineering, Accounting and Research) for ease of visualization.

textile products) to many short-lived arms races in 2-digit SIC industry 17 (special trade contractors). By construction, we observe at least one innovation arms race period in each of these 24 industries but for several ones, there is only one very short such period (eg.: 2-digit SIC industry 50 – wholesale trade durable goods).

Industry Characteristics of Innovation Arms Race Periods

We use nine variables to characterize industries along four dimensions. The sales-based Hirschman Herfindahl Index (HHI), the industry average ROA (avg ROA), the industry average $10NN$ HP similarity score (avg similarity score) and the industry average $10NN$ HP fluidity (avg fluidity) capture the degree of competition within the industry. The industry average firm size (measured by the log of total assets, denoted avg size) and the industry average capital intensity ratio (ratio of property, plant and equipment to total assets, denoted avg PPE) proxy for barriers to entry. We depict the nature of the industry technology by the industry average R&D intensity (ratio of R&D expenses to total assets, denoted avg R&D intensity), the industry average of the logarithm of one plus the number of patents (avg num patents) and the industry average of the logarithm of one plus the number of citations (num citations). Finally, because M&A contributes to resource reallocation between industry participants and reshapes industry competition, we account for the logarithm of one plus the number of M&A transactions in the industry (num M&A deals). The ratios are winsorized at the 1st and 99th percentiles before averaging and all industry characteristics are lagged by one year. Variable definitions and data sources are provided in Appendix Table A.1.

With these nine variables, we study industry characteristics correlated with the probability of witnessing an arms race period by estimating the following a logit regression specification:

$$ArmsRace_t^{Ind} = \frac{1}{1+\mathrm{e}^{-\left(\alpha+\beta_t+\boldsymbol{Characteristics_{t-1}^{Ind}}'\boldsymbol{\gamma}\right)}} \quad (16)$$

where we use the same notations as in Equations 14 and 15, bold notation are for vectors, β_t are year fixed-effects, $\boldsymbol{Characteristics_t^{Ind}}$ is the vector of selected industry-level time-varying characteristics and $\boldsymbol{\gamma}$ is the vector of coefficients of interest. Note that we do not include industry fixed-effects. Most of our nine industry characteristics are highly persistent through time and the inclusion of industry fixed-effects would mostly absorb them. Therefore, results reported in this section are exposed to the presence of omitted variables and descriptive by nature, with no aim of causal interpretation. Standard-errors are robust to heteroskedasticity.

Table 6 reports our results with nine specifications, designed to mitigate problems due to potentially strong collinearity between HP similarity scores and HP fluidity and between the measures of innovation. Columns 1 to 3 include both avg similarity score and avg fluidity (highly collinear, with a correlation coefficient of 0.74 in our sample). Columns 4 to 6 include avg similarity score only and Columns 7 to 9, avg fluidity only. Columns 1, 4 and 7 use avg R&D intensity to characterize the industry technology. Columns 2, 5 and 8 replace avg R&D intensity by avg num patents and Columns 3, 6 and 9, by avg num citations. While industry concentration (HHI) and asset tangibility (avg PPE) appear not to be related to innovation arms races between industry rivals, industries investing more in innovation (whether proxied by R&D, patents, or patent citations) are unambiguously more conducive environments, as expected. Industry-years displaying high M&A activity are also more prone to generate arms races, the reallocation of resources between industry participants apparently fostering this competitive behavior. Profitability (avg ROA) and firm size (avg size) appear also mostly positively correlated with future periods of arms races, even if statistical significance depends on regression specifications. On the contrary, industries featuring more similar products have innovation arms races less frequently—one possible rationale being that differentiation is more difficult and/or most costly to achieve in such context (Arrow, 1963). Finally, we note that industries with more dynamic product transformations (more fluid in HP vernacular) are also more prone to witness innovation arms races, but only if we condition on the degree of product similarity (Columns 1 to 3).

5. Additional investigations and Robustness checks

5.1. Responsive Investment Results Causal Interpretation

Instrumental Variables based Estimates

While it seems improbable that our test of the responsive investment prediction (Equations 6 and 7) is exposed to some simultaneity or reverse causality sources of bias (we lag our independent variable RICI by one year and therefore, future firm innovation investment decisions would have to drive past rival innovative acquisitions), potential endogenous omitted variables remain a concern. The issue is of importance because giving a causal interpretation to our results supporting the responsive investment prediction has policy implications: if rival innovative acquisitions drive firm investments in innovation higher, policymakers should not be too 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 rival innovative acquisitions and a firm's decision to invest in R&D and to acquire innovative targets are at play. Therefore, we decide to check the validity of the causal interpretation of our results using two instrumental variable approaches.

We first use the opportunity offered by the introduction of the U.S. federal R&D tax credit regulation in 1981 and its progressive implementation at U.S. states level. This staggered adoption process led 32 U.S. states to provide R&D tax credits by 2006. Hombert and Matray (2018) emphasize that these state level tax incentives 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 obtain firm level R&D user cost accounting from R&D state level tax incentives from Bloom et al. (2013) and use them to build a first instrument for RICI. Because our potentially endogenous variable of interest is computed for the firm 10 nearest neighbors rivals portfolio, we collect the R&D user cost for this same set of rival firms and take the average to obtain our instrument for $RICI_{i,t}$, denoted $R\&D_{i,t}^{TAX,NN10}$. Valid instruments must satisfy the relevance, exclusion, and independence assumptions. We argue that these are satisfied with $R\&D_{i,t}^{TAX,NN10}$:

- Relevance: R&D tax credits affect firm incentives to invest in R&D and, to the extent to which firms face funding constraints, we expect that changes in incentives to invest in R&D should correlate with changes in incentives to acquire innovative targets. Moreover, we anticipate that $R\&D_{i,t}^{TAX,NN10}$will be positively correlated with $RICI_{i,t}$ because, as explained above, a higher user cost of R&D should increase incentives (at least relatively speaking) to acquire innovation externally. This is a testable assumption.
- Exclusion: The instrument works through state's tax change that affects rivals located in that state, but not the focal firm because it is 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.

Our second instrument is based on firm commuting zone average R&D intensity. Firms located in a given commuting zone share many unobservables, such as the density of research facilities, presence of inventors and engineering schools, etc. These unobservables correlate with investments in innovation but are not under the direct control of any specific firm. Therefore, the variation of R&D intensity across commuting zones offers a source of exogenous variation in incentives to invest in innovation. We obtain our second instrument by computing the average commuting zone R&D intensity (defined as R&D divided by total assets) of the 10 nearest neighbor rival firms in the product market space, with exclusion of rivals in the same commuting zone as the focal firm's and denote it $R\&D_{i,t}^{CZ,NN10}$. We argue again that the $R\&D_{i,t}^{CZ,NN10}$ satisfies the relevance, exclusion and independence assumptions:

- Relevance: the correlation between rival investments in innovation and $R\&D_{i,t}^{CZ,NN10}$ finds its roots in the shared (more or less) conducive environment for innovative activities at the commuting zone level. This is a testable assumption.
- Exclusion: to compute the average commuting zone R&D intensity of the 10 nearest neighbors rival firms, we exclude rival firms that are located in the same commuting zone as the focal firm. This represents a powerful strategy to isolate rival firms' unobservables from the focal firm ones. Our regression specifications moreover include firm fixed effects that absorb firm level constant unobservables as well as numerous firm level time-varying control variables, that account for selection on observables.
- Independence: the focal firm chooses the set of products it brings to the market taking into account the rival firms' offerings and this is a clear channel that generates interdependence between firm product offerings. But many firms offer similar products in the product market space according to the Hoberg and Phillips (2010) similarity scores and minor variations in SEC 10K filing product descriptions impact similarity score based rankings of firms, generating exogenous variations in the 10 nearest neighbors rival firms portfolios composition. Rival firms included in the 10 nearest neighbors portfolio are as if randomly drawn from the cluster of firms close to each other in the product market space, at least for firms located in dense clusters. From this respect, our identification strategy is here analogous to so-called randomized buckets.

The identification of firms' commuting zones rests on zip codes collected in Compustat database, the use of the zip codes to county crosswalk table obtained from the Kaggle web site[15] and county to commuting zone matching file provided by David Dorn[16]. One source of complexity is that zip codes can belong to several commuting zones. When it is the case, we estimate the corresponding zip code R&D intensity as the average R&D intensity of the encompassing commuting zones.

[15] www.kaggle.com/datasets/danofer/zipcodes-county-fips-crosswalks.
[16] www.ddorn.net/data.htm.

From the econometric standpoint, we obtain our instrumental variable estimates using the 2SLS estimator. In the first stage, we regress $RICI_{i,t}$ on $R\&D_{i,t}^{TAX,NN10}$ or $R\&D_{i,t}^{CZ,NN10}$and all other control variables. Taking the case of $R\&D_{i,t}^{TAX,NN10}$as instrument, the first stage regressions are:

$$RICI_{i,t} = \alpha_i + \beta_t + \gamma \; R\&D_{i,t}^{TAX,NN10} + \; \delta \; IA_{it} + \mu \; R\&D_{i,t}^{TAX} + \; \boldsymbol{Controls'}_{\boldsymbol{i,t-1}} \, \boldsymbol{\mu} + \; \epsilon_{i,t} \quad (17)$$

or

$$RICI_{i,t} = \alpha_i + \beta_t + \gamma \; R\&D_{i,t}^{TAX,NN10} + \; \delta \; \; R\&D_{i,t} + \mu \; R\&D_{i,t}^{TAX} + \; \boldsymbol{Controls'}_{\boldsymbol{i,t-1}} \, \boldsymbol{\mu} + \; \epsilon_{i,t} \quad (18)$$

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 17 and $RICI_{i,t-1}^{fit,2}$ using Equation 18) and the firm own R&D user cost (denoted $R\&D_{i,t}^{TAX}$): [17]

$$R\&D_{i,t} = \alpha_i + \; \beta_t + \gamma \; RICI_{i,t-1}^{fit,1} + \delta \; R\&D_{i,t}^{TAX} + \mu \; IA_{it} + \boldsymbol{Controls'}_{\boldsymbol{i,t-1}} \, \boldsymbol{\nu} + \; \epsilon_{i,t} \quad (19)$$

$$IA_{i,t} = \alpha_i + \; \beta_t + \gamma \; RICI_{i,t-1}^{fit,2} + \delta \; R\&D_{i,t}^{TAX} + \mu \; R\&D_{i,t} + \boldsymbol{Controls'}_{\boldsymbol{i,t-1}} \, \boldsymbol{\nu} + \; \eta_{i,t} \quad (20)$$

Standard errors are clustered at the firm level and adjusted to take into account the two-stage nature of this procedure. When using $R\&D_{i,t}^{TAX,NN10}$ as instrument, we limit the period under investigation to 1996-2010 because the latest adoption of R&D tax credits by U.S. states in the Bloom et al (2013) dataset did so in 2006, keeping that way a 5 years post treatment period. Similar regressions are run when using $R\&D_{i,t}^{CZ,NN10}$ as instrument. One may finally wonder why we do not include both $R\&D_{i,t}^{TAX}$ and $R\&D_{i,t}^{CZ,NN10}$ instruments simultaneously in our regression specifications, thus permitting an overidentification test. This is because the use of the $R\&D_{i,t}^{TAX}$ significantly shortens the estimation period and it appears to us to be interesting to report results pertaining to the full period.

Results obtained using $R\&D_{i,t}^{TAX,NN10}$ as instrument are displayed in Table 7 Panel A and corresponding results using $R\&D_{i,t}^{CZ,NN10}$ are in Table 7 Panel B. Columns 1 and 2 are dedicated to the R&D part of the responsive investment prediction (corresponding to Column 1 in Table 3), reporting the first stage and second stage regression results respectively and Columns 3 and 4 to the innovative acquisitions part of the responsive investment prediction (corresponding to Column 2 in Table 3), reporting likewise first and second stages regression results respectively.

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[17] We do follow an IV identification strategy for the value decrease prediction because the arguments for reverse causality are unlikely (firms would need to increase investment in innovation in anticipation of a value decrease) and the Fama/French set of forward-looking control variables leave little room for omitted-variable bias.

Starting with the Panel A results, We see that in Columns 1 and 3, corresponding to the first stage estimates, the coefficient of $R\&D_{i,t}^{TAX,NN10}$ is positive and highly statistically significant, with a Fisher statistic close to 16, well above the Staiger and Stock (1997) recommended threshold: increases in rivals' user cost of R&D push rivals to undertake more innovative acquisitions. The coefficient on lagged instrumented RICI 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 0.185 and 0.841), 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 test of instrument relevance 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 increase their innovative acquisitions due to an increase in R&D user cost, 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). Moreover, Panel A results pertain to the 1996 to 2010 subperiod and are, in this respect, not directly comparable to Table 3 results.

In Panel B, using $R\&D_{i,t}^{CZ,NN10}$ as instrument, reported results cover the whole 1996 to 2019 period. The first stage estimates reported in Columns 1 and 3 confirm that $R\&D_{i,t}^{CZ,NN10}$ is a highly relevant instrument, with associated Fisher statistic around 25. The coefficient estimates are positive: the 10 nearest neighbors rival firms commuting zone R&D intensity is positively correlated with rival firms' innovative acquisitions, an intuitive result driven by an environment conducive to innovation. Second stage estimates reported in Columns 2 and 4 are consistent with Table 7 Panel A and Table 3 results: an increase in rival firms' intensity of innovative acquisition (RICI) leads to an increase in the focal firm R&D and innovative acquisitions. We note moreover that, while the estimated coefficient in Column 2 (the R&D equation) is still eight-fold higher than in Table 3 (0.063 versus 0.008), the one in Column 4 (the innovative acquisitions equation) is in the order of magnitude of Table 3 estimate (0.186 versus 0.122) and therefore less exposed to the Jiang (2017) critique from that respect.

These instrumental variable-based results confirm therefore that the positive relation between rivals' innovative acquisitions 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 provide an estimate of the magnitude of the causal relation only for compliers and for the specific periods under investigation.

Placebo Tests

In an additional effort to check whether our results are spurious or driven by to some latent factors correlated to rival innovative acquisitions and affecting multiple dimensions of firm behavior, we implement three placebo tests. In each case, we replace the dependent variable in Equation 6 by alternatives, a priori not subject to be impacted by rival innovative acquisitions (or at least less so in the short run): the ratio of sales and general administrative expenses (XSGA) to total sales, the ratio of cost of goods sold (COGS) to total sales and the ratio of working capital (WCAP) to total sales.

Results are reported in Table 7 Panel C. In Columns 4 to 7, we add R&D and IA as additional control variables. In no case do rival firms' intensity of innovative acquisition (RICI) coefficients reach the standard thresholds of statistical significance.

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 rival innovative acquisitions (RICI) and excess investments in innovation (R&D and innovative acquisitions). This 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 Kogan et al. (2017) dataset. 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 Kogan et al. data are available only up to 2017 at the time of this writing) and the three-year window over which patents and patents citations are cumulated, our analyzed period ends in 2014. Our results are therefore obtained for a limited subsample of 28,581 observations. 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 lnMBTA 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 innovative acquisitions, like in Table 3. A clear message emerges from these estimates: no decline in innovation investment efficiency is observable due to excess investment in R&D or innovative acquisitions under the pressure of rival innovative acquisitions. 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.

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 point towards the presence of omitted variables driving the correlation between rival innovative acquisitions and firm investments in innovation. To investigate whether this is the case, we replicate our baseline analyses (Table 3) on the extensive margin, that is keeping all firms, whether or not their 10 nearest neighbor 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 rival innovative acquisitions from our sample.

5.4. Value Based Analysis

Our measure of rivals' IA, RICI, is count-based (see Equation 1). A corresponding value-based measure of rival innovative acquisitions 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 innovative acquisitions (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. Instrumental variable-based results (Table I.A.5) 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 responsive investment prediction). Finally, innovation investment efficiency shows no sign of decline (Table I.A.6) and results obtained on the extensive margin are consistent with results obtained on the intensive margin (Table I.A.7).

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:

$$R\&D_{it} = \alpha_i + \beta_t + (SIC3_{it} \times \beta_t) + \gamma\, RICI_{it-1} + \delta\, IA_{it} + \boldsymbol{Controls'_{it-1}\, \mu} + \epsilon_{it} \quad (21)$$

where $SIC3_{it}$ are 3-digit SIC industry fixed effects and β_t are year fixed effects. Results are reported in Table I.A.8. Panel A that replicates Table 3 count-based analysis Columns 1 and 2 for the responsive investment prediction and Columns 5 and 6 for the value decrease prediction. 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 RICI, 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 value of rivals' total assets as an alternative scaling factor. This leads us to define a new measure of intensity of rival innovation acquisitions as:

$$RIAT_{it} = \frac{RIAV_{it}}{AggRAT_{it}} \quad (22)$$

where we use the same notations as in Equation 1 and $AggRAT_{it}$ is the sum of firm i product market space 10 nearest neighbor 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.9., where Columns 1 and 2 replicates Table 3 Columns 1 and 2 (tests of the responsive 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 responsive investment prediction uses R&D expenses collected in Compustat scaled by total assets as the dependent variable (see Equation 6) and is therefore our econometric specification 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.10 Column 1 displays the coefficient of RICI, our measure of rival innovative acquisition intensity, to be compared to Table 3 Column 1's result, and Column 2 displays 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. Value Effects of Acquisitions Driven by Rivals' Innovative Acquisitions

As a final step, we investigate whether innovation arms races affect value creation and its repartition between acquirers and targets in acquisitions. To this end, we report the results of cross-sectional regressions that relate acquirer, target and combined CAR's and the offer premium to rival innovative acquisitions, using the same set of M&A transactions as the one introduced in Table 1 (sample sizes vary however as a function of the dependent variable as CAR and offer premium are only available for listed firms). The intensity of rival innovative acquisitions is measured by RICI (see Equation1), estimated in the 10 nearest neighbors' similarity score cluster of the acquirer, and lagged by one year with respect to the M&A transaction announcement year. We include a set of control variables potentially affecting the CAR and offer premium (Firm Size, Cash Only, Stock Only, Financial Acquirer, Hostile, Number of Bidders and Same Industry), all defined in Appendix Table A.1 as well as acquirer industry, target industry, and year fixed-effects.

Results are reported in Table 11. Column 1 is for acquirer CAR, Column 2 for target CAR, Column 3 for combined CAR's and Column 4 for the offer premium. These results are consistent with the Google-Microsoft case: the intensity of rival innovative acquisitions (RICI*)* negatively impacts acquirer and combined CAR's and positively affects target CAR and the offer premium. All results are statistically significant at least at the 5% level despite the limited number of transactions including listed targets. Notably, the RICI variable's estimated coefficient is negative in Column 3 for combined CAR. This suggests that the negative effect on acquirer CAR and positive effect for the target is really driven by a wealth transfer from acquirer to target shareholders. Note finally that we obtain similar results using our value-based measure of rivals innovative acquisitions RIVI (see Table I.A.11), except that the coefficient of RIVI is not statistically significant for M&A transaction CAR.

7. Conclusion

The Arms Race Hypothesis predicts that investment in innovation increases under the pressure of rivals (the responsive 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 2019 period 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 sector (and, to a lesser extent, healthcare)and several industry-level characteristics conducive to innovations arms races (in particular, high investments in innovation, high M&A activity, high profitability and large firm size), while high product similarity appears to reduce such behavior among industry participants. 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. Complementary analyses uncover no evidence of decreased innovation investment efficiency, suggesting that innovation arms races transfer economic rents to consumer. Cumulative abnormal returns and offer premiums-based analyses confirm that, under the pressure of rival innovative acquisitions, acquirers are willing to pay more to acquire of innovative targets.

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.

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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.

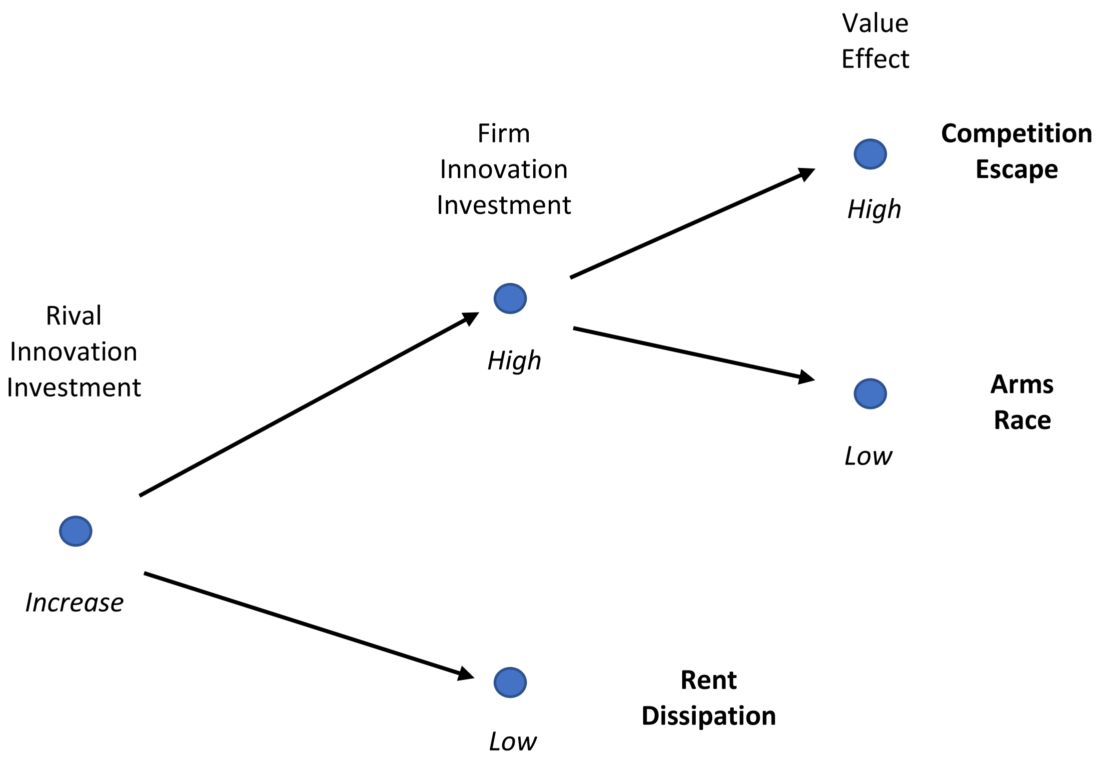

Figure 2 - Identification of Arms' Race Periods at the 2-digit SIC Industry Level

Figure 2 displays identified arms race periods by 2-digit SIC industry using the Markov-switching regressions-based approach described in Section 4.3. Each graphic is for one 2-digit SIC industry (the corresponding industry code is indicated in the graphic title). Years are reported on the horizontal axis and the corresponding probabilities to be in a high Markov regime on the vertical axis. The blue line pertains to the responsive investment prediction (Equation 14) and the red line to the value decrease prediction (Equation 15). Shaded areas are periods of innovation arms race.

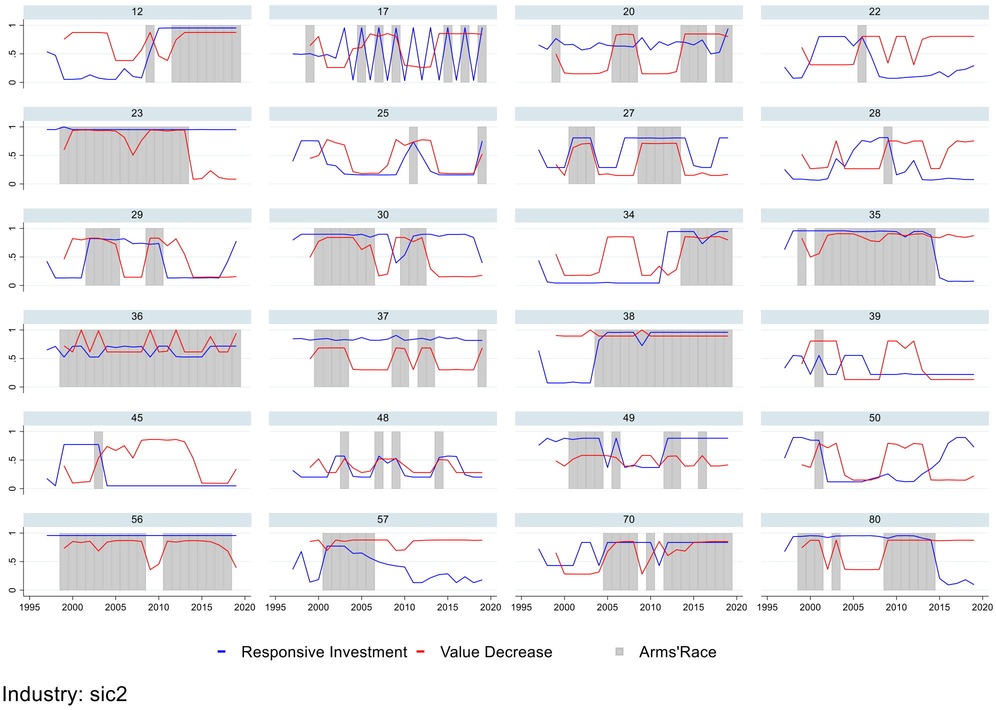

Table 1 – M&A Sample

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 Arms Race Hypothesis responsive investment prediction tests, Panel B on the value decrease tests, Panel C, on cumulative abnormal returns (CAR) cross-sectional regressions and Panel D on placebo 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 Appendix A.1.

Variable Name	Mean	Stdev.	25th Pctl.	Median	75th Pctl.	Observations
	1	2	3	4	5	6
Panel A – Responsive Investment Tests						
Dependent Variables						
R&D Intensity	0.049	0.094	0.000	0.003	0.062	59658
Innovative Acquisition	0.091	0.464	0.000	0.000	0.000	59658
Variables of Interest						
RICI	0.180	0.309	0.000	0.000	0.250	59658
Control Variables						
Firm Size	6.030	2.143	4.446	5.956	7.514	59658
ROA	0.069	0.187	0.045	0.106	0.159	59658
Leverage	0.209	0.189	0.017	0.182	0.341	59658
Liquidity	0.131	0.151	0.022	0.076	0.185	59658
Intangible Ratio	0.165	0.194	0.002	0.086	0.268	59658
MTB	3.160	4.200	1.185	1.970	3.459	59658
Panel B - Value decrease Tests						
Dependent Variables						
lnMTBA	0.272	0.647	-0.160	0.199	0.642	35204
Variables of Interest						
RICI	0.168	0.295	0.000	0.000	0.250	35204
Excess R&D	-0.001	0.035	-0.001	0.000	0.000	35204
Excess Innovative Acquisition	0.000	0.019	0.000	0.000	0.000	35204
Control Variables						
R&D Intensity	0.042	0.078	0.000	0.004	0.054	35204
Innovative Acquisition	0.097	0.465	0.000	0.000	0.000	35204
Historical R&D	0.042	0.076	0.000	0.004	0.056	35204
Historical Innovative Acquisition	0.013	0.041	0.000	0.000	0.001	35204
E_{it}/A_{it}	0.022	0.176	0.012	0.055	0.089	35204
dE_{it}/A_{it}	0.013	0.272	-0.025	0.010	0.043	35204
dE_{it+2}/A_{it}	0.014	0.268	-0.029	0.010	0.052	35204
dA_{it}/A_{it}	0.082	0.429	-0.032	0.114	0.269	35204
dA_{t+2}/A_{t}	0.235	0.808	-0.049	0.105	0.311	35204
dRD_{it}/A_{it}	0.002	0.056	0.000	0.000	0.004	35204
dRD_{it+2}/A_{it}	0.007	0.063	0.000	0.000	0.004	35204
I_{it}/A_{it}	0.013	0.015	0.001	0.009	0.019	35204
dI_{it}/A_{it}	0.001	0.014	-0.002	0.000	0.003	35204
dI_{it+2}/A_{it}	0.003	0.027	-0.002	0.000	0.004	35204
D_{it}/A_{it}	0.012	0.037	0.000	0.000	0.014	35204
dD_{it}/A_{it}	0.002	0.045	0.000	0.000	0.001	35204
dD_{it+2}/A_{it}	0.002	0.040	0.000	0.000	0.002	35204
dV_{it+2}/A_{it}	0.402	2.265	-0.205	0.130	0.623	35204

Panel C - CAR Tests						
Dependent Variables						
Acquirer CAR (-2, +2)	0.006	0.071	-0.026	0.003	0.036	33081
Target CAR (-2, +2)	0.265	0.257	0.094	0.215	0.393	1738
Combined CAR (-2, +2)	0.019	0.077	-0.024	0.012	0.056	1564
Offer Premium	0.487	0.450	0.216	0.394	0.662	2153
Variables of Interest						
RICI	0.206	0.314	0.000	0.000	0.333	33081
Control Variables						
Firm Size	6.554	2.149	5.056	6.494	7.964	33081
Cash Only	0.271	0.445	0.000	0.000	1.000	33081
Stocky Only	0.078	0.268	0.000	0.000	0.000	33081
Same Industry	0.572	0.495	0.000	1.000	1.000	33081
Financial Acquirer	0.046	0.209	0.000	0.000	0.000	33081
Hostile Deal	0.001	0.033	0.000	0.000	0.000	33081
Number of Bidders	1.005	0.091	1.000	1.000	1.000	33081
Panel D – Placebo Tests						
Dependent Variables						
SG&A	0.337	0.538	0.103	0.224	0.393	59658
COGS	0.795	1.944	0.467	0.642	0.775	59658
WC	0.183	0.420	0.096	0.175	0.266	58752
Panel E – Industry Level Characteristics						
HHI	0.107	0.080	0.054	0.092	0.127	693
Avg. ROA	0.084	0.058	0.062	0.098	0.120	693
Avg. Similarity Score	0.166	0.036	0.134	0.162	0.194	693
Avg. Fluidity	6.187	1.966	4.681	5.778	7.499	693
Avg. Size	6.524	0.986	5.809	6.430	7.181	693
Avg. PPE	0.323	0.183	0.169	0.247	0.499	693
Avg. R&D Intensity	0.028	0.038	0.003	0.011	0.033	693
Avg. Num Patents	1.962	0.672	1.500	1.956	2.397	693
Avg. Num Citations	2.631	1.472	1.409	2.826	3.792	693

Table 3 - Innovation Arms Race Hypothesis Responsive Investment and Value decrease Predictions Tests
Table 3 reports results of innovation Arms Race Hypothesis predictions (see Figure 1). Columns 1 to 4 are dedicated to the responsive 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 the focal 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 the 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 (1998). 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 focal 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 acquisitions of the focal firm and Historical Innovative Acquisition (the average of Innovative acquisitions 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.

Focal Firms'	R&D Intensity	Innovative Acquisition	R&D Intensity	Innovative Acquisition	Market Value	
	1	2	3	4	5	6
RICI	0.008***	0.123***	0.008***	0.123***	0.031*	0.049**
	0.001	0.000	0.001	0.000	0.071	0.027
RICI x Excess R&D					-0.602**	
					0.042	
RICI x Historical R&D					0.127	
					0.630	
RICI x Excess Innovative Acquisition						-0.060***
						0.000
RICI x Historical Innovative Acquisition						-0.042**
						0.014
Innovative Acquisition	-0.001				0.028***	0.055***
	0.165				0.005	0.000
R&D Intensity		-0.092			1.598***	1.502***
		0.136			0.000	0.000
Control Variables	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	59658	59658	59658	59658	35204	35204
Adjusted R^2	0.816	0.195	0.816	0.195	0.712	0.712

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

Table 4 replicates Table 3 tests of the Innovation Arms Race Hypothesis 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 responsive investment prediction. 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 focal 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 (1998). 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 focal firm and 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 focal firm and Historical Innovative Acquisition (the average innovative acquisitions 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

Focal Firms'	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4
RICI	0.008***	0.114***	0.034**	0.048**
	0.001	0.000	0.045	0.017
RICI x Excess R&D			-0.600**	
			0.041	
RICI x Historical R&D			0.086	
			0.741	
RICI x Excess Innovative Acquisition				-0.070***
				0.000
RICI x Historical Innovative Acquisition				-0.043**
				0.039
Innovative Acquisition	-0.001*		0.025**	0.056***
	0.096		0.011	0.000
R&D Intensity		-0.102*	1.621***	1.522***
		0.079	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	58196	58196	34415	34415
Adjusted R^2	0.816	0.190	0.711	0.711

Panel B - Acquisitions of Public Targets Only

Focal Firms'	R&D Intensity	Innovative Acquisition		Firm Value
	1	2	3	4
RICI	0.003**	0.004*	-0.009	-0.007
	0.048	0.096	0.662	0.451
RICI x Excess R&D			-1.023**	
			0.028	
RICI x Historical R&D			0.001	
			0.995	
RICI x Excess Innovative Acquisition				-0.092**
				0.013
RICI x Historical Innovative Acquisition				-0.038
				0.442
Innovative Acquisition	0.001		0.016	0.042
	0.806		0.567	0.199
R&D Intensity		0.003	1.577***	1.522***
		0.808	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	59658	59658	35204	35204
Adjusted R^2	0.816	0.051	0.712	0.711

Panel C - Horizontal Transactions

Focal Firms'	R&D Intensity	Innovative Acquisition		Firm Value
	1	2	3	4
RICI	0.009***	0.110***	0.014	0.017
	0.000	0.000	0.364	0.379
RICI x Excess R&D			-0.621**	
			0.029	
RICI x Historical R&D			0.048	
			0.839	
RICI x Excess Innovative Acquisition				-0.023
				0.176
RICI x Historical Innovative Acquisition				0.009
				0.638
Innovative Acquisition	-0.002**		0.016**	0.028**
	0.036		0.042	0.047
R&D Intensity		-0.116**	1.637***	1.537***
		0.041	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	45436	45436	28329	28329
Adjusted R^2	0.812	0.203	0.707	0.707

Table 5 – Innovation Arms Race Responsive Investment and Value Decrease Predictions Tests – Industry Level Analyses

Table 5 replicates Table 3 tests of the Innovation Arms Race Hypothesis predictions (see Figure 1) at the industry level. We use the Fama-French 5 industry classification, based on the correspondence table with 4-digit SIC codes provided by the authors, to identify industry activities and the average 3-digit SIC industry return on assets (ROA) to discriminate between high and low pre-existing industry rent industries. Panels A and B focus on *by industry* analyses and Panel C focuses on *High-Low Industry Rent.* High (Low) pre-existing industry rent industries are industries in the highest (lowest) quartile of the 3-digit SIC industry average ROA distribution in a given year.

Panel A reports the results for the responsive investment prediction, whereas the dependent variable is R&D Intensity in columns (1) to (5), defined as R&D expenses divided by total assets and Innovative Acquisition in Column (6) to (10), defined as the number of innovative target acquisitions divided by the number of acquisitions by the focal firm.

Panel B reports the results for the value decrease prediction, where 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 (1998). In both the panels, the variables of interest are RICI or the interaction between RICI and Excess R&D or Excess Innovative Acquisition, like in Table 3.

Columns (1) and (2) in Panel C report the results for responsive investment prediction, and column (3) and (4) of the same Panel reports the results for the value decrease prediction. In Panel C, the variables of interest are interacted with dummy variables identifying high (low) pre-existing rent industries. 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 focal 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 focal firm and Historical Innovative Acquisition (the average innovative acquisitions 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 - Responsive investment prediction

Subject Firms'	R&D Intensity					Innovative Acquisition				
	1	2	3	4	5	6	7	8	9	10
	Cons.	Manuf.	High-Tech	Health	Others	Cons.	Manuf.	High-Tech	Health	Others
RICI	0.002	0.001	0.009***	0.011**	0.002	0.01	0.02	0.149***	0.048	0.093***
	0.377	0.573	0.002	0.036	0.401	0.417	0.28	0.001	0.169	0.002
Innovative Acquisition	-0.001	0.000	-0.001	-0.001	-0.004**					
	0.379	0.78	0.314	0.523	0.047					
R&D Intensity						-0.172	0.041	-0.116	-0.077	-0.500*
						0.374	0.783	0.29	0.52	0.083
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12032	14599	16600	5944	10046	12032	14599	16600	5944	10046
Adjusted R^2	0.783	0.778	0.747	0.796	0.896	0.15	0.157	0.201	0.2	0.158

Panel B – Value decrease prediction

Subject Firms'	Firm Value									
	Cons.		Manuf.		High-Tech		Health		Others	
	1	2	3	4	5	6	7	8	9	10
RICI	0.069**	0.054*	0.019	0.012	-0.012	0.014	-0.018	0.005	0.111**	0.083*
	0.029	0.085	0.542	0.604	0.693	0.607	0.56	0.852	0.031	0.093
RICI x Excess R&D	-1.609		-0.258		-0.131		-0.843*		0.311	
	0.365		0.793		0.686		0.08		0.811	
RICI x Historical R&D	-1.578		0.093		0.173		0.1		-0.444	
	0.197		0.885		0.544		0.699		0.458	
RICI x Excess Innovative Acquisition		-0.065		-0.031		-0.031*		-0.033		-0.034
		0.36		0.529		0.097		0.338		0.557
RICI x Historical Innovative Acquisition		-0.201*		0.102		-0.03		-0.046		0.128**
		0.088		0.193		0.317		0.198		0.019
Innovative Acquisition	0.032	0.052**	0.033*	0.038**	0.008	0.024**	0.015	0.032	0.147***	0.152***
	0.152	0.048	0.06	0.049	0.321	0.026	0.329	0.184	0.000	0.002
R&D Intensity	3.505***	3.135***	2.796***	2.753***	0.984***	0.995***	2.330***	2.133***	0.697	0.709
	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.320	0.314
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7415	7415	9350	9350	9357	9357	3496	3496	5409	5409
Adjusted R^2	0.763	0.762	0.708	0.709	0.697	0.697	0.68	0.679	0.733	0.733

Panel C – High-Low Industry Rent

Focal Firms'	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4
RICI			0.031*	0.048**
			0.070	0.027
RICI x High Rent	0.000	0.106**		
	0.795	0.027		
RICI x Low Rent	0.009***	0.213***		
	0.000	0.000		
RICI x Others	-0.001	0.059***		
	0.551	0.001		
RICI x Excess R&D x High Rent			-5.448**	
			0.033	
RICI x Excess R&D x Low Rent			-0.463	
			0.100	
RICI x Excess R&D x Others			-1.594**	
			0.023	
RICI x Excess Innovative Acquisition x High Rent				-0.039
				0.516
RICI x Excess Innovative Acquisition x Low Rent				-0.062***
				0.000
RICI x Excess Innovative Acquisition x Others				-0.028
				0.299
RICI x Historical Innovative Acquisition				-0.041**
				0.016
RICI x Historical R&D			0.128	
			0.625	
Innovative Acquisition	-0.001		0.028***	0.054***
	0.100		0.004	0.000
R&D Intensity		-0.108*	1.602***	1.503***
		0.073	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	59658	59658	35204	35204
Adjusted R^2	0.816	0.200	0.712	0.712
F-tests				
$High\ Rent - Low\ Rent\ \neq 0$	-0.009***	-0.107*	-4.985*	0.023
$High\ Rent - Others\ \neq 0$	0.001	0.047	-3.854	-0.011
$Low\ Rent - Others\ \neq 0$	0.010***	0.154***	1.131*	-0.034

Table 6 – Innovation Arms Race Hypothesis predictions – Industry Level Characteristics

Table 6 reports industry level characteristics correlated with innovation arms race periods using the Markov switching regressions based approach described in Section 4.3. The dependent variable is $\mathrm{ArmsRace}_t^{\mathrm{Ind}}$, an indicator variable equal to 1 if the corresponding industry is in an arms race state during the corresponding year and zero otherwise. Columns correspond to different specifications that account for collinearity between the industry level time varying characteristics accounted for. All industry characteristics are lagged by one year with respect to innovation arms race periods identification. Year fixed effects are included in all specifications. All variable definitions are provided in Appendix Table A.1. Estimates are obtained using a logit specification. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

	1	2	3	4	5	6	7	8	9
HHI	0.813	-3.888	-3.280	1.051	-3.856	-3.317	0.054	-4.371*	-3.871*
	0.680	0.120	0.169	0.557	0.101	0.145	0.974	0.054	0.078
Avg. ROA	17.004***	5.810**	5.461*	11.054***	2.627	2.458	10.561***	3.608	3.341
	0.000	0.037	0.052	0.001	0.276	0.319	0.002	0.162	0.202
Avg. Similarity Score	-45.127***	-25.551***	-25.648***	-19.567***	-7.953*	-8.745**			
	0.000	0.001	0.001	0.000	0.055	0.033			
Avg. Fluidity	0.544***	0.366***	0.353**				-0.156**	-0.037	-0.053
	0.000	0.008	0.011				0.041	0.592	0.448
Agv. Size	0.569***	0.174	0.330*	0.554***	0.203	0.338*	0.506***	0.188	0.327*
	0.002	0.397	0.079	0.002	0.288	0.059	0.002	0.310	0.056
Avg. PPE	1.604	-0.667	-1.022	1.558	-0.984	-1.244	-0.210	-1.887**	-2.151***
	0.104	0.480	0.272	0.109	0.287	0.174	0.789	0.019	0.007
Avg. R&D Intensity	25.895***			23.880***			20.507***		
	0.000			0.000			0.000		
Avg Num Patents		0.544**			0.499**			0.528**	
		0.018			0.027			0.016	
Avg Num Citations			0.266*			0.238			0.251*
			0.082			0.110			0.082
Num M&A Deals	0.821***	0.609***	0.654***	0.861***	0.633***	0.681***	0.751***	0.559***	0.611***
	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001	0.000
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	693	597	597	693	597	597	693	597	597
Pseudo R^2	0.203	0.172	0.166	0.185	0.164	0.158	0.159	0.158	0.152

Table 7 – The Arms Race Hypothesis Responsive Investment Prediction Test – Causal Interpretation
Table 7 replicates Table 3 tests of the Innovation Arms Race Hypothesis responsive investment prediction using an instrumental variable approach (Panels A and B) and alternative dependent variables (Panel C) as placebo tests. 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 Panel A, RICI is instrumented by the 10 nearest neighbors rival firms R&D user cost accounting for state level tax incentives ($R\&D_{i,t}^{TAX,NN10}$) as in Bloom et al. (2013) and Hombert and Matray (2018). In Panel B, RICI is instrumented using the average commuting zone R&D intensity (defined as R&D divided by total assets) of the 10 nearest neighbors rival firms in the product market space, with exclusion of rivals in the same commuting zone as the focal firm one ($R\&D_{i,t}^{CZ,NN10}$). In Panels A and B, 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 the focal firm), estimates are obtained using the 2SLS estimator and Columns 1 and 3 report the results from first stage regressions and Columns 2 and 4 display the results from second stage regressions. In Panel C, the dependent variables are SG&A (sales and general administrative expenses divided by total sales), COGS (cost of goods sold divided by total sales) and WC (working capital divided by total sales), respectively in Columns 1 and 4, 2 and 5, 3 and 6, and R&D and IA are added as control variables in Columns 4 to 6. 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 – Tax Incentives Program Based Instrument

	1st Stage	*2nd Stage*	*1st Stage*	*2nd Stage*
	RICI	R&D Intensity	RICI	Innovative Acquisition
	1	2		2
$R\&D_{i,t}^{TAX,NN10}$	0.208***		0.207***	
	0.000		0.000	
RICI		0.185***		0.841***
		0.000		0.004
Innovative Acquisition	0.041***	-0.008***		
	0.000	0.000		
R&D Intensity			0.255***	-0.319***
			0.000	0.002
$R\&D_{i,t}^{TAX}$	0.037	-0.049***	0.045	-0.140
	0.511	0.002	0.416	0.219
Joint test of excluded instruments F(9,7406)	35.97		34.15	
Prob >F				
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	41734	41734	41734	41734
Overall R^2		0.213		0.028
Chi²		489.04		143.72

Panel B – 10 Nearest Neighbors Rival Commuting Zone Average R&D Intensity Based Instrument

	1st Stage	*2nd Stage*	*1st Stage*	*2nd Stage*
	RICI	R&D Intensity	RICI	Innovative Acquisition
	1	2		2
$R\&D_{i,t}^{CZ,NN10}$	2.118***		2.112***	
	0.000		0.000	
RICI		0.063**		0.186**
		0.034		0.015
Innovative Acquisition	0.188***	-0.016***		
	0.000	0.004		
R&D Intensity			0.215***	-0.088***
			0.001	0.001
$R\&D_{i,t}^{CZ}$	0.693	-0.012	0.806	0.412*
	0.163	0.896	0.126	0.076
Joint test of excluded instruments F(9,6575)	41.51		34.38	
Prob >F	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	57878	57878	57878	57878
Overall R^2		0.291		0.032
Chi^2		792.53		532.03

Panel C- Placebo Analyses

Focal Firms'	SG&A	COGS	WC	SG&A	COGS	WC
	1	2	3	4	5	6
RICI	0.006	-0.053	0.007	0.000	-0.067	0.010
	0.648	0.253	0.419	0.966	0.152	0.268
Innovative Acquisition				0.000	-0.014**	0.000
				0.879	0.024	0.966
R&D Intensity				0.767***	1.868**	-0.400***
				0.000	0.016	0.004
Control Variables	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	59658	59658	58752	59658	59658	58752
Adjusted R^2	0.631	0.654	0.502	0.634	0.655	0.504

Table 8 – The Innovation Arms Race and 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 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 focal firm and 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 focal 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

Focal Firms'	Number of Patents	
	1	2
RICI	-0.019*	-0.004
	0.075	0.638
RICI x Excess R&D	-0.011	
	0.919	
RICI x Historical R&D	0.168**	
	0.032	
RICI x Excess Innovative Acquisition		-0.010
		0.363
RICI x Historical Innovative Acquisition		-0.009
		0.437
Innovative Acquisition	0.001	0.005
	0.879	0.389
R&D Intensity	0.186*	0.205**
	0.068	0.022
Control Variables	Yes	Yes
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	28581	28581
Adjusted R^2	0.905	0.905

Panel B – Citation based

Focal Firms'	Number of Citations	
	1	2
RICI	-0.133***	-0.045
	0.009	0.237
RICI x Excess R&D	0.468	
	0.421	
RICI x Historical R&D	1.393***	
	0.003	
RICI x Excess Innovative Acquisition		-0.071
		0.201
RICI x Historical Innovative Acquisition		0.078
		0.319
Innovative Acquisition	0.063***	0.083***
	0.006	0.002
R&D Intensity	0.163	0.460
	0.700	0.280
Control Variables	Yes	Yes
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	28581	28581
Adjusted R^2	0.868	0.868

Table 9 – Innovation Arms Race Hypothesis Responsive Investment and Value decrease Predictions Tests – Extensive Margin Analyses

Table 9 displays results of the innovation Arms Race Hypothesis 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 acquisitions pressure). Columns 1 and 2 are dedicated to the responsive investment prediction. 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 the focal 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 (1998). 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 focal firm and 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 focal firm and 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.

Focal Firms'	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4
RICI	0.005**	0.111***	0.033**	0.040**
	0.031	0.000	0.032	0.041
RICI x Excess R&D			-0.596**	
			0.015	
RICI x Historical R&D			0.001	
			0.995	
RICI x Excess Innovative Acquisition				-0.065***
				0.000
RICI x Historical Innovative Acquisition				-0.047***
				0.008
Innovative Acquisition	-0.001		0.028***	0.056***
	0.147		0.002	0.000
R&D Intensity		-0.064	1.401***	1.300***
		0.123	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	81390	81390	47038	47038
Adjusted R^2	0.818	0.204	0.709	0.709

Table 10 – Value Effects of Acquisitions Driven by Rivals' Innovative Acquisitions

Table 10 displays results of cross-sectional regressions acquirer, target and combined announcement cumulative abnormal returns (CAR) and offer premium on rival innovative acquisitions and control variables. The sample of M&A transactions is introduced in Table 1. CAR are obtained using the market model as return generating process, an estimation window of 250 days (with at least 100 valid returns) that ends 41 days before the M&A announcement date and a 5 days centered event window using to the Wharton Research Data Services Analytics (WRDS) Event Study tool. The dependent variable is the acquirer CAR in Column 1, target CAR in Column 2, transaction CAR in Column 3 and the 4 weeks offer premium in Column 4, collected in the Thomson Reuter (now Refinitiv) SDC database (SDC). Sample sizes vary from columns to columns because CAR and offer premiums are only available for listed firms. The variable of interest is the rival intensity of innovative acquisition, denoted RICI (see Equation 1), lagged by one year with respect to the M&A announcement year, estimated in the 10 nearest neighbors similarity score cluster of the acquirer. The control variables include Firm Size (natural logarithm of total assets), Cash Only (a dummy variable equal to one for full cash payment transaction), Stock Only (a dummy variable equal to one for full stock payment transaction), Same Industry (a dummy variable equal to one when the acquirer and the target share the same 2-digit SIC code), Financial Acquirer (a dummy variable equal to one for acquisition by financial acquirers), Hostile (a dummy variable equal to one for transactions reported as hostile in SDC), and Number of Bidders (the number of bidders according to SDC). Standard-errors are robust to heteroskedasticity. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

	Acquirer CAR	Target CAR	Combined CAR	Offer Premium
	1	2	3	4
RICI	-0.006***	0.040**	-0.013**	0.092***
	0.000	0.046	0.045	0.003
Control Variables				
Firm Size	-0.003***	0.004	-0.007***	-0.010*
	0.000	0.238	0.000	0.097
Cash Only	0.005***	0.117***	0.021***	0.121***
	0.000	0.000	0.000	0.000
Stocky Only	-0.004*	-0.030*	-0.024***	-0.015
	0.059	0.064	0.000	0.605
Same Industry	-0.001	-0.001	0.000	-0.010
	0.452	0.953	0.914	0.621
Financial Acquirer	0.000	-0.009	0.001	-0.077*
	0.858	0.787	0.944	0.084
Hostile Deal	0.001	0.104**	0.041***	0.011
	0.921	0.049	0.010	0.863
Number of Bidders	-0.006	-0.077***	0.004	0.187***
	0.124	0.000	0.568	0.000
Year Fixed Effects	Yes	Yes	Yes	Yes
Acquirer Industry Fixed Effects	Yes	Yes	Yes	Yes
Target Industry Fixed Effects	Yes	Yes	Yes	Yes
Observations	33081	1738	1564	2153
Adjusted R^2	0.012	0.129	0.106	0.082

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 responsive investment prediction tests and Panel B, on the variables used in value decrease tests.

Variable Name	Definitions
Panel A - Responsive Investment Tests	
Dependent Variables	
R&D Intensity	It is defined as R&D expenses divided by total assets (*Source: Compustat and CRSP*).
Innovative Acquisition	It is defined as the number of innovative target acquisitions divided by the number of acquisitions by focal firm (*Source: SDC*).
Variables of Interest	
RICI	It is defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (*Source: SDC*).
Control Variables	
Firm Size	It is defined as the natural logarithm of total assets (*Source: Compustat and CRSP*).
ROA	It is defined as the ratio of operating income before depreciation to total assets (*Source: Compustat and CRSP*).
Leverage	It is defined as the ratio of long-term debt and debt in current liabilities to total assets (*Source: Compustat and CRSP*).
Liquidity	It is a cash ratio and is defined as the ratio of cash position to total assets (*Source: Compustat and CRSP*).
Intangible Ratio	It is defined as the ratio of intangible assets to total assets (*Source: Compustat and CRSP*).
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 (*Source: Compustat and CRSP*).
Panel B - Value decrease Tests	
Dependent Variables	
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 (*Source: Compustat and CRSP*).
Variables of Interest	
RICI	It is defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (*Source: SDC*).
Excess R&D	It is defined as the difference between R&D Intensity of the focal firm and its historical R&D Intensity (the average R&D Intensity over the last three years) (*Source: Compustat and CRSP*).
Excess Innovative Acquisition	It is defined as the difference between Innovative Acquisition of the focal firm and its historical Innovative Acquisition (the average Innovative Acquisition over the last three years) (*Source: SDC*).
Control Variables	
R&D Intensity	It is defined as R&D expenses divided by total assets (*Source: Compustat and CRSP*).
Innovative Acquisition	It is defined as the number of innovative target acquisitions divided by the number of acquisitions by focal firm (*Source: SDC*).
Historical R&D	It is defined as (the average R&D Intensity over the last three years) (*Source: Compustat and CRSP*).

Historical Innovative Acquisition	It is defined as the average Innovative Acquisition over the last three years (*Source: SDC*).
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* (*Source: Compustat and CRSP*).
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* (*Source: Compustat and CRSP*).
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* (*Source: Compustat and CRSP*).
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* (*Source: Compustat and CRSP*).
dA_{t+2}/A_{t}	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* (*Source: Compustat and CRSP*).
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* (*Source: Compustat and CRSP*).
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* (*Source: Compustat and CRSP*).
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* (*Source: Compustat and CRSP*).
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* (*Source: Compustat and CRSP*).
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* (*Source: Compustat and CRSP*).
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 (*Source: Compustat and CRSP*).
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* (*Source: Compustat and CRSP*).
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* (*Source: Compustat and CRSP*).
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* (*Source: Compustat and CRSP*).
Panel C - CAR Analyses Tests	
Dependent Variables	
Acquirer CAR	Acquirer CAR are obtained using the market model as return generating process, an estimation window of 250 days (with at least 100 valid returns) that ends 41 days before the M&A announcement date and a 5 days centered event window thanks to the Wharton Research Data Services Analytics (WRDS) Event Study tool (Source: Compustat and CRSP).

Target CAR	Target CAR are obtained using the market model as return generating process, an estimation window of 250 days (with at least 100 valid returns) that ends 41 days before the M&A announcement date and a 5 days centered event window thanks to the Wharton Research Data Services Analytics (WRDS) Event Study tool (Source: Compustat and CRSP).
Combined CAR	The combined CAR is a value weighted CAR and weights are calculated based on market value of each firm (Source: Compustat and CRSP).
Offer Premium	Offer price relative to target market price four weeks prior to M&A announcement (Source: SDC).
Variables of Interest	
RICI	It is defined as the number of innovative target acquisitions divided by the total number of acquisitions by rival firms per year (*Source: SDC*).
Control Variables	
Firm Size	It is defined as the natural logarithm of total assets (*Source: Compustat and CRSP*).
Cash Only	It is a dummy variable equal to one for full cash payment transaction (Source: SDC).
Stocky Only	It is a dummy variable equal to one for full stock payment transaction (Source: SDC).
Same Industry	It is a dummy variable equal to one when the acquirer and the target share the same 2-digit SIC code (Source: SDC).
Financial Acquirer	It is a dummy variable equal to one for acquisition by financial acquirers (Source: SDC).
Hostile Deal	It is a dummy variable equal to one for transactions reported as hostile in SDC (Source: SDC).
Number of Bidders	It is defined as the number of bidders (Source: SDC).
Panel D – Placebo Tests	
SG&A	Sales and general administrative expenses divided by total sales (Source: Compustat)
COGS	Cost of goods sold divided by to total sales (Source: Compustat)
WC	Working capital divided by total sales. Working capital is calculated as inventory plus accounts receivable, and minus accounts payable (Source: Compustat)
Panel E – Industry Level Characteristics	
HHI	The sum of squares of sales-based market shares (*Source: Compustat and CRSP*).
Avg. ROA	The industry average ROA. ROA is defined as the ratio of operating income before depreciation to total assets (*Source: Compustat and CRSP*).
Avg. Similarity Score	The industry average $10NN$ HP similarity scores (Source: Hoberg and Phillips (2010).
Avg. Fluidity	The industry average $10NN$ HP fluidity scores (Source: Hoberg and Phillips (2010).
Avg. Size	The industry average firm size. Size is defined as the natural logarithm of total assets (*Source: Compustat and CRSP*).
Avg. PPE	The industry average of capital intensity ratio, defined as the ratio of property, plant and equipment to total assets (*Source: Compustat and CRSP*).

Avg. R&D Intensity	The industry average of R&D intensity ratio, defined as the ratio of R&D expenses to total assets (*Source: Compustat and CRSP*).
Avg. Num Patents	The industry average of the logarithm of one plus the number of patents *(Source: Kogan et al. (2017)).*
Avg. Num Citations	The industry average of the logarithm of one plus the number citations *(Source: Kogan et al. (2017)).*
Num M&A Deals	The natural logarithm of one plus the number of M&A transactions in the industry *(Source: SDC).*

Appendix A.2: Innovation Arms Race Process Anticipations

The econometric specifications that we introduce in Equations 8 and 9 to test the Arms Race Hypothesis 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 neighbors 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 acquirer, 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 is 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:

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

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

Results are reported in Table A.3 and are without ambiguities. In the absence of fixed effects (Column 1 using a 3 days centered event window, the γ coefficient is positive and statistically significant. This is inconsistent 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 our sample size. It is worthwhile to note that year fixed effects are already enough to generate these 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.3 - 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 focal 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 the dummy variable D_{it} equal to one in case of rival innovative acquisition (See Equation A.2.1). Estimates are obtained using the classic ordinary least square (OLS) estimator. 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.

Focal Firms'	CAR (-1, +1)			
	1	2	3	4
Rival Innovative Acquisition	0.245***	0.097	-0.007	-0.016
	0.002	0.216	0.940	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 7 in the paper, with the variable interest based on value of transactions (*RIVI)*.

Table I.A. 6 reports the baseline results from Table 8 in the paper, with the variable interest based on value of transactions (*RIVI)*.

Table I.A. 7 reports the baseline results from Table 9 in the paper, with the variable interest based on value of transactions (*RIVI)*.

Table I.A. 8 - reports the baseline results from Table 3 in the paper, with the addition of Industry x Year Fixed Effects.

Table I.A. 9 - reports the baseline results from Table 3 in the paper, with the with the variable interest alternatively defined *(RIAT).*

Table I.A. 10 tests The Responsive Investment Prediction (incentives to innovate) using multiple imputation analysis*.*

Table I.A.11 reports the baseline results from Table 10 in the paper, with the variable interest based on value of transactions (*RIVI)*.

Table I.A. 1 - Innovation Arms Race Hypothesis Predictions Tests

Table I.A. 1 reports results of innovation Arms Race Hypothesis 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 responsive 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 the focal 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 the 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 (1998). 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 focal 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 acquisitions of the focal firm and Historical Innovative Acquisition (the average of Innovative acquisitions 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.

Focal Firms'	R&D Intensity	Innovative Acquisition	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4	5	6
RICI	0.008***	0.123***	0.008***	0.123***	0.031*	0.049**
	0.001	0.000	0.001	0.000	0.071	0.027
RICI x Excess R&D					-0.602**	
					0.042	
RICI x Historical R&D					0.127	
					0.630	
RICI x Excess Innovative Acquisition						-0.060***
						0.000
RICI x Historical Innovative Acquisition						-0.042**
						0.014
Innovative Acquisition	-0.001				0.028***	0.055***
	0.165				0.005	0.000
R&D Intensity		-0.092			1.598***	1.502***
		0.136			0.000	0.000
Control Variables						
Firm Size	-0.009***	-0.006	-0.009***	-0.005		
	0.000	0.431	0.000	0.495		
ROA	-0.077***	0.041*	-0.077***	0.048**		
	0.000	0.093	0.000	0.033		
Leverage	-0.011***	-0.106***	-0.011***	-0.105***		
	0.002	0.000	0.003	0.000		
Liquidity	0.007	-0.002	0.007	-0.003		
	0.141	0.936	0.140	0.919		
Intangible Ratio	-0.009**	-0.178***	-0.009*	-0.177***		
	0.048	0.000	0.052	0.000		
MTB	0.000	0.002**	0.000	0.002**		
	0.126	0.032	0.125	0.027		
E_{it}/A_{it}					0.452***	0.458***
					0.000	0.000
dE_{it}/A_{it}					0.071**	0.070**

					0.015	0.017
dE_{it+2}/A_{it}					0.089***	0.089***
					0.005	0.005
dA_{it}/A_{it}					0.121***	0.125***
					0.000	0.000
dA_{it+2}/A_{it}					0.221***	0.221***
					0.000	0.000
dRD_{it}/A_{it}					0.067	0.025
					0.565	0.833
dRD_{it+2}/A_{it}					0.770***	0.774***
					0.000	0.000
I_{it}/A_{it}					-1.621*	-1.564*
					0.066	0.078
dI_{it}/A_{it}					0.050	0.008
					0.928	0.989
dI_{it+2}/A_{it}					-0.938*	-0.933*
					0.078	0.082
D_{it}/A_{it}					1.528***	1.526***
					0.000	0.000
dD_{it}/A_{it}					0.070	0.072
					0.662	0.654
dD_{it+2}/A_{it}					0.754***	0.755***
					0.001	0.001
dV_{it+2}/A_{it}					-0.070***	-0.070***
					0.000	0.000
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59658	59658	59658	59658	35204	35204
Adjusted R^2	0.816	0.195	0.816	0.195	0.712	0.712

Table I.A. 2 - Innovation Arms Race Hypothesis Predictions

Table I.A. 2 reports results of innovation Arms Race Hypothesis 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 responsive 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 the focal 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. 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 the 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 (1998). 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 focal 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 acquisitions of the focal firm and Historical Innovative Acquisition (the average of Innovative acquisitions 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.

Focal Firms'	R&D Intensity	Innovative Acquisition	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4	5	6
RIVI	0.006***	0.168***	0.006***	0.167***	0.021	0.046***
	0.001	0.001	0.001	0.002	0.181	0.008
RIVI x Excess R&D					-0.416	
					0.174	
RIVI x Historical R&D					0.203	
					0.384	
RIVI x Excess Innovative Acquisition						-0.023***
						0.002
RIVI x Historical Innovative Acquisition						-0.022**
						0.014
Innovative Acquisition	0.000				0.005*	0.017***
	0.179				0.098	0.003
R&D Intensity		-0.165			1.583***	1.546***
		0.175			0.000	0.000
Control Variables	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	52983	52983	52983	52983	31319	31319
Adjusted R^2	0.814	0.16	0.814	0.159	0.713	0.713

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

Table I.A. 3 replicates Table 3 tests of the Innovation Arms Race Hypothesis 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 responsive investment prediction. 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 focal 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 (1998). 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 focal firm and 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 focal firm and Historical Innovative Acquisition (the average innovative acquisitions 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

Focal Firms'	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4
RIVI	0.006***	0.159***	0.020	0.047***
	0.001	0.002	0.270	0.006
RIVI x Excess R&D			-0.305	
			0.338	
RIVI x Historical R&D			0.235	
			0.335	
RIVI x Excess Innovative Acquisition				-0.023***
				0.002
RIVI x Historical Innovative Acquisition				-0.021**
				0.032
Innovative Acquisition	0.000		0.005	0.016***
	0.157		0.133	0.005
R&D Intensity		-0.175	1.550***	1.540***
		0.151	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	51181	51181	30336	30336
Adjusted R^2	0.814	0.153	0.711	0.711

Panel B - Acquisitions of Public Targets Only

Focal Firms'	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4
RIVI	0.004**	0.017	-0.006	-0.002
	0.042	0.196	0.792	0.850
RIVI x Excess R&D			-0.927*	
			0.060	
RIVI x Historical R&D			0.019	
			0.925	
RIVI x Excess Innovative Acquisition				-0.012
				0.155
RIVI x Historical Innovative Acquisition				-0.010
				0.529
Innovative Acquisition	0.000		-0.002	0.001
	0.515		0.746	0.848
R&D Intensity		0.040	1.605***	1.558***
		0.520	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	52983	52983	31319	31319
Adjusted R^2	0.813	0.027	0.712	0.712

Panel C - Horizontal Transactions

Focal Firms'	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4
RIVI	0.010***	0.200***	-0.007	0.020
	0.000	0.001	0.698	0.204
RIVI x Excess R&D			-0.357	
			0.202	
RIVI x Historical R&D			0.310	
			0.259	
RIVI x Excess Innovative Acquisition				-0.005
				0.643
RIVI x Historical Innovative Acquisition				0.001
				0.926
Innovative Acquisition	-0.001		0.000	0.004
	0.109		0.977	0.676
R&D Intensity		-0.186	1.592***	1.599***
		0.112	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	36565	36565	22663	22663
Adjusted R^2	0.807	0.169	0.706	0.705

Table I.A.4 – Innovation Arms Race Responsive Investment and Value Decrease Prediction Tests – Industry Level Analyses

Table I.A. 4 replicates Table 3 tests of the Innovation Arms Race Hypothesis predictions (see Figure 1) at the industry level. In contrast to Table 5 in the paper, the variable of interest here is based on the dollar value of transaction instead of the count. We use the Fama-French 5 industry classification, based on the correspondence table with 4-digit SIC codes provided by the authors, to identify homogenous industry activities and the average 3-digit SIC industry return on assets (ROA) to discriminate between high and low pre-existing industry rent industries. Panels A and B focus on *by industry* analyses and Panel C focuses on *High-Low Industry Rent.* High (Low) pre-existing industry rent industries are industries in the highest (lowest) quartile of the 3-digit SIC industry average ROA distribution in a given year.

Panel A reports the results for the responsive investment prediction, whereas the dependent variable is R&D Intensity in columns (1) to (5), defined as R&D expenses divided by total assets and Innovative Acquisition in Column (6) to (10), defined as the number of innovative target acquisitions divided by the number of acquisitions by focal firm.

Panel B reports the results for the value decrease prediction, whereas 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 (1998). In both the panels, the variables of interest are RICI or the interaction between RICI and Excess R&D or Excess Innovative Acquisition.

Columns (1) and (2) in Panel C report the results for the responsive investment prediction, and column (3) and (4) of the same Panel reports the results for the value decrease prediction. In Panel C, the variables of interest are interacted with dummy variables identifying high (low) pre-existing rent industries. *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 focal 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 focal firm and Historical Innovative Acquisition (the average innovative acquisitions 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 - Responsive investment prediction

Subject Firms'	R&D Intensity					Innovative Acquisition				
	1	2	3	4	5	6	7	8	9	10
	Cons.	Manuf.	High-Tech	Health	Others	Cons.	Manuf.	High-Tech	Health	Others
RIVI	0.000	0.000	0.008***	0.007*	0.003	0.018	0.002	0.225***	0.144*	0.140**
	0.770	0.780	0.002	0.072	0.143	0.478	0.957	0.001	0.055	0.014
Innovative Acquisition	0.000	0.000	-0.001	-0.001	-0.002**					
	0.718	0.434	0.209	0.411	0.011					
R&D Intensity						-0.163	0.298	-0.288	-0.240	-0.961**
						0.723	0.468	0.219	0.420	0.036
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9977	13181	15397	5372	8620	9977	13181	15397	5372	8620
Adjusted R^2	0.786	0.788	0.747	0.796	0.885	0.078	0.097	0.176	0.187	0.070

Panel B – Value decrease prediction

Subject Firms'	Firm Value									
	Cons.		Manuf.		High-Tech		Health		Others	
	1	2	3	4	5	6	7	8	9	10
RIVI	0.029	0.009	-0.004	0.009	0.005	0.020	-0.019	0.021	0.126**	0.086*
	0.299	0.661	0.883	0.607	0.864	0.324	0.521	0.399	0.017	0.082
RIVI x Excess R&D	-1.329		0.525		-0.302		-0.520		0.641	
	0.239		0.604		0.419		0.298		0.553	
RIVI x Historical R&D	-1.373		0.436		0.060		0.190		-1.122*	
	0.145		0.324		0.825		0.505		0.059	
RIVI x Excess Innovative Acquisition		-0.018		0.004		-0.026***		-0.015		-0.040
		0.360		0.792		0.010		0.289		0.312
RIVI x Historical Innovative Acquisition		-0.068		0.013		-0.021		-0.033*		0.042*
		0.132		0.689		0.171		0.070		0.095
Innovative Acquisition	0.011*	0.015**	0.011*	0.010*	-0.002	0.013**	0.001	0.011	0.052**	0.067*
	0.053	0.021	0.085	0.065	0.614	0.035	0.772	0.211	0.047	0.068
R&D Intensity	3.572***	3.254***	2.746***	2.882***	1.024***	0.996***	2.400***	2.320***	0.659	0.634
	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.354	0.378
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6174	6174	8466	8466	8688	8688	3181	3181	4624	4624
Adjusted R^2	0.762	0.762	0.708	0.708	0.703	0.703	0.686	0.685	0.731	0.731

Panel C – High-Low Industry Rent

Focal Firms'	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4
RIVI			0.021	0.035**
			0.178	0.032
RIVI x High Rent	0.000	0.124**		
	0.992	0.011		
RIVI x Low Rent	0.006***	0.366***		
	0.001	0.000		
RIVI x Others	-0.001	0.112***		
	0.622	0.000		
RIVI x Excess R&D x High Rent			-1.551	
			0.507	
RIVI x Excess R&D x Low Rent			-0.339	
			0.265	
RIVI x Excess R&D x Others			-1.015	
			0.104	
RIVI x Excess Innovative Acquisition x High Rent				0.057
				0.246
RIVI x Excess Innovative Acquisition x Low Rent				-0.001
				0.905
RIVI x Excess Innovative Acquisition x Others				0.026
				0.178
RIVI x Historical Innovative Acquisition				0.015
				0.310
RIVI x Historical R&D			0.200	
			0.387	
Innovative Acquisition	-0.001*		0.005*	0.005
	0.057		0.095	0.112
R&D Intensity		-0.229*	1.586***	1.544***
		0.053	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	59658	59658	31319	31319
Adjusted R^2	0.816	0.165	0.713	0.712
F-tests				
$High\ Rent - Low\ Rent\ \neq 0$	-0.006***	-0.242***	-1.212	0.058
$High\ Rent - Others\ \neq 0$	0.001	0.012	-0.536	0.031
$Low\ Rent - Others\ \neq 0$	0.005***	0.254***	0.676	0.025

Table I.A. 5 - The Arms Race Hypothesis Responsive Investment Prediction – Instrumental Variable Estimates

Table I.A. 5 replicates Table 7 tests of the Innovation Arms Race Hypothesis responsive investment prediction using an instrumental variable approach. 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 Panel A, RIVI is instrumented by the 10 nearest neighbors rival firms R&D user cost accounting for state level tax incentives ($R\&D_{i,t}^{TAX,NN10}$) as in Bloom et al. (2013) and Hombert and Matray (2018). In Panel B, RIVI is instrumented using the average commuting zone R&D intensity (defined as R&D divided by total assets) of the 10 nearest neighbors rival firms in the product market space, with exclusion of rivals in the same commuting zone as the focal firm one ($R\&D_{i,t}^{CZ,NN10}$). In each panel, 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 the focal firm. Estimates are obtained using the 2SLS estimator. Columns 1 and 3 report the results from first stage regressions and Columns 2 and 4 display the results from second stage regressions. 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 – Tax Incentives Program Based Instrument

	1st Stage	*2nd Stage*	*1st Stage*	*2nd Stage*
	RIVI	R&D Intensity	RIVI	Innovative Acquisition
	1	2		2
$R\&D_{i,t}^{TAX,NN10}$	0.121*		0.121*	
	0.082		0.085	
RIVI		0.225***		1.213
		0.001		0.167
Innovative Acquisition	0.210***	-0.005***		
	0.000	0.001		
R&D Intensity			0.187**	-0.480**
			0.033	0.047
$R\&D_{i,t}^{TAX}$	0.089	-0.069***	0.092	-0.241
	0.229	0.005	0.212	0.442
Joint test of excluded instruments F(9,7406)	30.45		27.55	
Prob >F				
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	37361	37361	37361	37361
Overall R^2		0.162		0.028
Chi^2		369.27		167.30

Panel B – 10 Nearest Neighbors Rival Commuting Zone Average R&D Intensity Based Instrument

	1st Stage	*2nd Stage*	*1st Stage*	*2nd Stage*
	RIVI	R&D Intensity	RIVI	Innovative Acquisition
	1	2		2
$R\&D_{i,t}^{CZ,NN10}$	2.250***		2.263***	
	0.000		0.000	
RIVI		0.065**		0.118*
		0.039		0.062
Innovative Acquisition	0167***	-0.016***		
	0.000	0.003		
R&D Intensity			0.214***	-0.058***
			0.002	0.007
$R\&D_{i,t}^{CZ}$	0.612	-0.030	0.591	-0.312**
	0.287	0.750	0.316	0.037
Joint test of excluded instruments F(9,6575)	34.98		31.40	
Prob >F	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	57878	57878	57878	57878
Overall R^2		0.263		0.014
Chi^2		772.25		334.40

Table I.A. 6 - The Innovation Arms Race and Innovation Efficiency

Table I.A. 6 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 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 focal firm and 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 focal 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

Focal Firms'	Number of Patents	
	1	2
RIVI	-0.015	-0.002
	0.108	0.793
RIVI x Excess R&D	0.099	
	0.376	
RIVI x Historical R&D	0.164*	
	0.053	
RIVI x Excess Innovative Acquisition		-0.004
		0.284
RIVI x Historical Innovative Acquisition		-0.003
		0.567
Innovative Acquisition	0.000	0.002
	0.862	0.420
R&D Intensity	0.153	0.201**
	0.135	0.029
Control Variables	Yes	Yes
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	25445	25445
Adjusted R^2	0.906	0.906

Panel B – Citation based

Focal Firms'	Number of Citations	
	1	2
RIVI	-0.104**	-0.017
	0.017	0.564
RIVI x Excess R&D	0.590	
	0.209	
RIVI x Historical R&D	1.238**	
	0.010	
RIVI x Excess Innovative Acquisition		-0.046**
		0.013
RIVI x Historical Innovative Acquisition		0.011
		0.738
Innovative Acquisition	0.017*	0.040***
	0.051	0.008
R&D Intensity	0.204	0.520
	0.655	0.243
Control Variables	Yes	Yes
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	25445	25445
Adjusted R^2	0.870	0.870

Table I.A. 7 - Innovation Arms Race Hypothesis Predictions – Extensive Margin Analyses

Table I.A. 7 displays results of the innovation Arms Race Hypothesis 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 acquisitions 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 responsive investment prediction. 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 the focal 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 (1998). 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 focal firm and 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 focal firm and 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.

Focal Firms'	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4
RIVI	0.003*	0.158***	0.019	0.035**
	0.055	0.001	0.123	0.017
RIVI x Excess R&D			-0.531**	
			0.044	
RIVI x Historical R&D			0.085	
			0.623	
RIVI x Excess Innovative Acquisition				-0.029***
				0.000
RIVI x Historical Innovative Acquisition				-0.025***
				0.004
Innovative Acquisition	-0.001*		0.006**	0.020***
	0.079		0.038	0.000
R&D Intensity		-0.140*	1.376***	1.306***
		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	81390	81390	47038	47038
Adjusted R^2	0.818	0.161	0.709	0.709

Table I.A. 8 - Innovation Arms Race Hypothesis Predictions – Industry x Year Fixed Effects

Table I.A. 8 replicates Table 3 tests of the innovation Arms Race Hypothesis 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 responsive 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 focal 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 focal 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 focal 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

Focal Firms'	R&D Intensity	Innovative Acquisition	Firm Value	
	1	2	3	4
RICI	0.005***	0.036***	0.002	0.015
	0.000	0.001	0.914	0.284
RICI x Excess R&D			-0.558*	
			0.055	
RICI x Historical R&D			0.085	
			0.726	
RICI x Excess Innovative Acquisition				-0.032***
				0.006
RICI x Historical Innovative Acquisition				-0.030
				0.126
Innovative Acquisition	-0.002**		0.019**	0.034***
	0.042		0.020	0.001
R&D Intensity		-0.164**	1.674***	1.578***
		0.018	0.000	0.000
Control Variables	Yes	Yes	Yes	Yes
Indus x Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	57712	57712	33754	33754
Adjusted R^2	0.810	0.183	0.737	0.737

Panel B – Value based

Focal Firms'	R&D Intensity	Innovative Acquisition	Market Value	
	1	2	5	6
RIVI	0.004***	0.058**	0.001	0.019**
	0.001	0.029	0.972	0.022
RIVI x Excess R&D			-0.427	
			0.170	
RIVI x Historical R&D			0.143	
			0.456	
RIVI x Excess Innovative Acquisition				-0.017**
				0.022
RIVI x Historical Innovative Acquisition				-0.017*
				0.067
Innovative Acquisition	-0.001***		0.004	0.013**
	0.008		0.186	0.016
R&D Intensity		-0.380***	1.642***	1.586***
		0.007	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	51043	51043	29864	29864
Adjusted R^2	0.806	0.140	0.737	0.737

Table I.A. 9 - Innovation Arms Race Hypothesis Predictions – Alternative definition of variable of interest
Table I.A. 9 replicates Table 3 tests of the innovation Arms Race Hypothesis 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 responsive 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 focal 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 focal 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 focal 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.

Focal Firms'	R&D Intensity	Innovative Acquisition	Market Value	
	1	2	5	6
RIAT	0.014*	0.926***	0.218**	0.427**
	0.088	0.001	0.044	0.011
RIAT x Excess R&D			-3.392**	
			0.013	
RIAT x Historical R&D			1.813*	
			0.084	
RIAT x Excess Innovative Acquisition				-0.072**
				0.036
RIAT x Historical Innovative Acquisition				-0.081**
				0.032
Innovative Acquisition	0.000		0.004	0.011**
	0.241		0.205	0.033
R&D Intensity		-0.140	1.577***	1.527***
		0.238	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	52983	52983	31319	31319
Adjusted R^2	0.813	0.160	0.714	0.713

Table I.A. 10 - Innovation Arms Race Hypothesis Predictions – Multiple Imputation Analyses

Table I.A. 10 tests the responsive 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.

Focal Firms'	R&D Intensity	
	1	2
RICI	0.008***	
	0.000	
RIVI		0.006***
		0.000
Control Variables	Yes	Yes
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	55507	45877
Adjusted R^2	0.816	0.816

Table I.A.11 – Value Effects of Acquisitions Driven by Rivals' Innovative Acquisitions

Table I.A. 11 displays results of cross-sectional regressions acquirer, target and transaction of M&A announcement cumulative abnormal returns (CAR) and offer premium on rival innovative acquisitions and control variables. In contrast with Table 10 in the paper, the variable of interest is based on the dollar value of transaction. The sample of M&A transactions is introduced in Table 1. CAR are obtained using the market model as return generating process, an estimation window of 250 days (with at least 100 valid returns) that ends 41 days before the M&A announcement date and a 5 days centered event window using to the Wharton Research Data Services Analytics (WRDS) Event Study tool. Offer premium is collected in SDC and is defined as the offer price relative to target market price four weeks prior to M&A announcement. The dependent variable is the acquirer CAR in Column 1, target CAR in Column 2, transaction CAR in Column 3 and the 4 weeks offer premium in Column 4, collected in the Thomson Reuter (now Refinitiv) SDC database (SDC). Sample sizes vary from columns to columns because CAR and offer premiums are only available for listed firms. 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). It is lagged by one year with respect to acquirer announcement year. The control variables include Firm Size (natural logarithm of total assets), Cash Only (a dummy variable equal to one for full cash payment transaction), Stock Only (a dummy variable equal to one for full stock payment transaction), Same Industry (a dummy variable equal to one when the acquirer and the target share the same 2-digit SIC code), Financial Acquirer (a dummy variable equal to one for acquisition by financial acquirers), Hostile (a dummy variable equal to one for transactions reported as hostile in SDC), and Number of Bidders (the number of bidders according to SDC). Standard errors are robust to heteroskedasticity. All variable definitions are provided in Appendix Table A.1. Statistical significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

	Acquirer CAR	Target CAR	Combined CAR	Offer Premium
	1	2	3	4
RIVI	-0.004***	0.045**	-0.008	0.071**
	0.001	0.012	0.143	0.010
Control Variables				
Firm Size	-0.003***	0.004	-0.007***	-0.010*
	0.000	0.230	0.000	0.094
Cash Only	0.005***	0.118***	0.021***	0.123***
	0.000	0.000	0.000	0.000
Stocky Only	-0.004*	-0.029*	-0.024***	-0.010
	0.055	0.068	0.000	0.630
Same Industry	-0.001	-0.001	0.000	-0.990
	0.463	0.968	0.916	0.630
Financial Acquirer	0.000	-0.009	0.001	-0.077*
	0.873	0.776	0.936	0.084
Hostile Deal	0.001	0.104**	0.041**	0.011
	0.919	0.047	0.010	0.867
Number of Bidders	-0.006	-0.078***	0.004	0.185***
	0.128	0.000	0.566	0.000
Year Fixed Effects	Yes	Yes	Yes	Yes
Acquirer Industry Fixed Effects	Yes	Yes	Yes	Yes
Target Industry Fixed Effects	Yes	Yes	Yes	Yes
Observations	33081	1738	1564	2153
Adjusted R^2	0.012	0.13	0.105	0.081