Intellectual Property Protection in M&A Negotiations[†]

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In this paper, I show that a major share of the value of target firm's intellectual property can be protected from expropriation by the acquirer through negotiating a compensating bidder termination fee (BTF), which is paid to the target in case the acquirer abandons the deal. I apply a capitalization model for intangible capital stocks to proxy for the component of intellectual property in target firm's market value. The results suggest that, on average, for every dollar of target firm's R&D capital stock, roughly 16 cents of protective share is incorporated in the BTF. I strengthen my causal interpretation with an instrument variables approach that exploits exogenous industry-level variation in R&D worker quota. The relation between target firm's innovation activity and BTF size is more pronounced, if the target is a pioneer in its technology sector, if the target operates in an industry that sells unique products, if the target is assigned to the hightech or healthcare industry, and if the target mentions "trade secrets" in its 10-K report filed with the SEC prior to deal announcement. The effect is further increasing in the degree of technological proximity as well as product market rivalry between acquirer and target. Extending prior research at the intersection of innovation, law, and M&A, this paper concludes that BTFs serve as a contract mechanism that provide target firms compensation for revelation of sensitive information in M&A negotiations if acquirers terminate deals. The option to include BTFs in M&A contracts thereby increases acquirers' incentives to close the deal and increases targets' ex-ante incentives to reveal innovative secret information.

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JEL classification: G14, G34, O34

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1 Introduction

"In recent decades, for example, the fraction of the total output of our economy that is essentially conceptual rather than physical has been rising. This trend has, of necessity, shifted the emphasis in asset valuation from physical property to intellectual property and to the legal rights inherent in intellectual property."

Keynote Speech by Alan Greenspan, former Chair of the Federal Reserve of the United States, about Intellectual Property Rights at the Stanford Institute for Economic Policy Research Economic Summit, Stanford, California, February 27, 2004.

"The future of the nation depends in no small part on the efficiency of industry, and the efficiency of industry depends in no small part on the protection of intellectual property."

Richard A. Posner, Judge on the U.S. Court of Appeals for the Seventh Circuit, in Rockwell Graphic Systems, Inc. v. DEV Industries, Inc., 925 F.2d 174 (1991) [Nr. 17].

Since the late 1970s, intangible assets have become an increasingly important factor of production, whereas physical and financial assets more and more became commodities. At the same time, intellectual property evolved to play a more central role in mergers and acquisitions, where synergistic gains in product markets and technological innovations have found to be among the main reasons why these corporate acquisitions take place (e.g., Bena and Li (2014), Frésard, Hoberg, and Phillips (2020), and Hoberg and Phillips (2010)). Simultaneuously, intellectual property is notoriously hard to value and has traditionally been seen as an asset inextricably linked to the business and revenues of the firm.

Whether it is the trade secret of a beverage producer's unique recipe, the (ongoing) R&D results of a cancer drug developed by a pharmaceutical company, the patent portfolio of a technology company, or the customer data and algorithms of an internet company – intellectual property is nowadays often one of the most important assets of targets in M&A deals and firms in general.

A second trend underlining the significance of intellectual property in M&A is that the market for buying and selling these assets has become more liquid over time. Thus, not only is the value of intellectual property difficult to estimate (e.g., Kogan et al. (2017)), it is also no longer inevitably bound to the firm where it is generated.

Firms have an incentive to invest in innovation and into their organization to generate intellectual property if they can also reap the benefits that are expected to materialize in the future. From a legislator's perspective it is thus important to provide the economy with a functioning legal system on which firms can rely on their intellectual property to be protected. As a consequence, trade secret law has evolved from the common law of unfair competition, and developed over time to prohibit misappropriation of important technology and business secrets[1], and patent law has established rules to protect a particular implementation of an idea[2].

In M&A, acquirers increasingly select targets to gain access to their innovations and to commercialize them (Phillips and Zhdanov (2013), Bena and Li (2014), and Frésard et al. (2020)). Gaining insights into these sensitive information begins with the start of the M&A process and signing of confidentiality/non-disclosure agreements (NDAs): the longer and the more intense the private and public takeover process, the more information about the target firm is revealed to the acquirer. The protection of sensitive information is particularly relevant for R&D-intense targets that might generate major shares of their future revenues through their patents, trade secrets, and other intellectual property.

Intellectual property of the target that should be protected from expropriation in M&A negotiations includes trade secrets, transferable knowledge applied in (not already granted) patents[3], and even so-called "negative" information. Trade secrets – as a special form of intellectual property – encompass any "information, including a formula, pattern, compilation, program, device, method, technique, or process that (1) derives independent economic value, actual or potential, from not being generally known to, and not being readily ascertainable by

[1] Most important legislation in this area comprises the Uniform Trade Secrets Act (UTSA), published by the Uniform Law Commission (ULC) in 1979 and amended in 1985, later enacted in all U.S. states, as well as the Inevitable Disclosure Doctrine (IDD), adopted by many U.S. courts since the mid-1990s. The UTSA does not distinguish between tangible and memorized trade secrets.

[2] See, e.g., Economic Report of the President (2006), and Gould and Gruben (1996). Beyond trade secrets and patents, innovators can also rely on copyrights and trademarks to protect their intellectual property. Legislators often have to outweigh the benefits for innovating firms versus the associated costs for society, such as the potential for creating monopoly power and the restrictions on exploiting useful technologies.

[3] Successfully granted patents itself are already legally protected and give the owner the exclusive right to exclude others from copying, using, and selling the invention for a limited period of time.

proper means by, other persons who can obtain economic value from its disclosure or use, and (2) is the subject of efforts that are reasonable under the circumstances to maintain its secrecy." (National Conference of Commissioners on Uniform State Laws (1985)). I.e., trade secrets only exist if their secrecy is preserved and can comprise both technical as well as business information[4]. "Negative" information refers to, e.g., designs that didn't work[5]: "The definition includes information that has commercial value from a negative viewpoint, for example the results of lengthy and expensive research which proves that a certain process will not work could be of great value to a competitor." (National Conference of Commissioners on Uniform State Laws (1985)). More precisely, these can be dead-ends encountered in research and development, relinquished technical solutions, details of unsuccessful efforts to remedy problems in manufacturing certain products, and also failed attempts to spark sales of the firm's products. If not properly protected, competitors could expropriate it without bearing the costs and risks associated with its development, resulting in an ex-ante deterrent of firms to innovate.

Thus, if mergers are closed successfully, the acquirer obtains all control and property rights of the target firm, including its intellectual property. In these cases, no protection of target firms' intellectual property from expropriation by acquirers would've been needed, since the property rights are de jure transferred.

Nevertheless, it remains an open question how target firms' intellectual property can be protected in – sometimes intense – M&A negotiations, especially if acquirers later terminate deals under their control and walk away with sensitive information about the target's business, that, in some cases, can be vital to its very existence.

[4] Many firms rely on trade secrets, rather than patents, as their primary, most valuable innovation. Reasons to not patent include, e.g., that patenting is costly (especially for small firms – application costs are low, but patent litigation and other legal issues may be expensive), that their most valuable innovation is simply not "patentable", or firms voice concerns about the legal enforcement of patents (see, e.g., Athreye and Fassio (2018) for a comprehensive study on why firms decide to not patent). Besides technical trade secrets, business secrets can be marketing and sales as well as advertising plans, competitors' (re-) actions, (key) personnel information, customer and supplier data, internal cost and pricing information, market analyses, and unannounced financial and business-related information, among others.

[5] Yet, even if it runs directly contrary to the principles of competition in a capitalistic society, "negative" information receives the same protection as trade secrets, although this issue is under current discussion by legal scholars (see, e.g., Khoury (2014)).

This paper suggests that the protection of target firms' sensitive intellectual property can be achieved in M&A by negotiating a bidder termination fee (BTF). Bidder termination fees[6] are cash payments from the acquirer to the target, in case the acquirer terminates the pending deal due to reasons under his control[7], and are usually negotiated by target firm's management during the private takeover process. BTFs are becoming legally binding with the signing of the merger agreement between the two parties, and are thought to compensate the target for the direct and indirect costs incurred if the deal is terminated. Direct costs are costs such as fees for financial and legal deal advisors, consulting firms, opportunity costs of the assets involved and other transaction fees. Indirect costs are, most important, above mentioned costs of information expropriation, and other private information about future synergies on which competitors can potentially free ride on. This paper's central prediction hence is:

The higher the value of target firm's intellectual property,
the higher the negotiated bidder termination fee.

Main Findings

I find that – controlling for a wide array of covariates that reliably affect the size of the BTF – the value of target firm's intellectual property, as proxied by accumulated R&D expenses as a fraction of the firm's market value prior to deal announcement, is significantly positively related to the size of the BTF. The estimated relation is also economically important as a one-standard deviation increase in this target firm R&D intensity measure is associated with a 0.57% increase in the size of the BTF. BTF size is defined as the USD (mm) amount of the negotiated bidder termination fee, divided by the market capitalization (also in USD mm) of the target firm 42 trading days prior to offer announcement. A back-of-the-envelope calculation suggests that, on average, for every dollar of target firm's R&D capital stock, roughly 16 cents of protective fee is incorporated in the BTF. I regard this a protective share, since the target receives a legal claim on this compensation payment in case of bidder terminated deals – representing an insurance-like payment for (likely) intellectual property revelation.

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[6] The terms "bidder termination fee (BTF)", "acquirer termination fee (ATF)", and "reverse termination fee (RTF)" can be used interchangeably. I use the term "bidder termination fee" throughout this paper.
[7] Reasons are discussed in Section 2.

Further test reveal that the relation between target firm's intellectual property value and BTF size is more pronounced, if the target is a pioneer in its technology sector, as proxied by its knowledge capital stock growth rate prior to offer announcement. At early stages, sensitive R&D outcomes are likely not yet legally protected through patenting[8], so the risk of revealing them at this stage is highest, since without patenting them there exists no claim under patent law. The effect is also stronger if the target is in an industry that produces unique products, if the target is assigned to the hightech or healthcare industry, and if the target mentions “trade secret”, “trade secrets” and/or “trade secrecy” in its most recent 10-K report filed with the SEC prior to deal announcement. I moreover find that the relation is increasing in the degree of technological proximity as well as product market rivalry between acquirer and target. This confirms the theoretical prediction that the target's private intellectual property might be of highest value for an acquirer that has a similar knowledge base and is competing with the target in similar product markets.

Utilizing an event study of target firms' stock price reactions at the resolution date of the deal reveals that the stock market reacts, on average, significantly less negative if acquirers abandon deals and if the negotiated bidder termination fee is high. This deal cancellation effect not only holds for bidder's termination announcement and the associated de jure claim of the target to receive the BTF, but also for the announced de facto realized payment of the BTF to the target. This result strengthens the reasoning that the BTF has a protective, insurance-like component priced in, providing the target with a payment if acquirers abandon deals due to reasons under their sphere of control.

Contribution to the Literature

A key methodological contribution of this paper is the application of an instrumental variables estimation to instrument the value of target firm's intellectual property. I suggest two candidates as valid instruments, but focus on one specifically, namely the share of employees working in strictly R&D-related jobs as a fraction of all jobs in target firm's SIC2 industry.

[8] The average duration from filing a patent (patent application) until receiving a patent grant is roughly 2–3 years (20–32 months, depending on the workload required to process, see the current wait time statistics at the USPTO website: https://www.uspto.gov/dashboards/patents/main.dashxml (permanent link)).

Tests show that this industry-level instrument is likely uncorrelated with deal-level BTF size and only correlated with BTF size through its correlation with target's knowledge capital stock. The results are thus robust to endogeneity concerns, in particular omitted variable bias and reverse causality. Pancost and Schaller (2019) further suggest that, in practice, the instrumental variables approach also resolves a substantial amount of attenuation bias resulting from classical errors-in-variables in linear regressions. Consistent with their findings, I find that the marginal effect between target's knowledge capital stock and BTF size increases with the instrumental variables estimation. Exploiting this source of exogenous variation strengthens the causal interpretation of this paper.

This paper belongs to the growing body of work that emphasizes the important role of innovation in mergers and acquisitions. Phillips and Zhdanov (2013) model and empirically test how an active M&A market and competition affect the decision to conduct R&D and innovate. They find that smaller firms optimally may decide to innovate more when they can sell out to larger firms, and larger firms may find it disadvantageous to engage in a "R&D race" with smaller firms, as they can obtain access to innovation through acquisitions. Contrary to standard industrial organization theory (e.g., Dasgupta and Stiglitz (1980)[9]), their model suggests a positive relation between innovation and competitive pressure – but less so for large firms: M&A provides a strong ex-ante incentive for small firms to innovate aggressively, but a competitve market itself decreases large firms' odds of successfully innovating themselves. I add to their findings by hightlighting the role of bidder termination fees in R&D-driven M&A.

Frésard et al. (2020) examine determinants of vertical acquisitions using product text linked to vocabulary from input-output tables and propose that the innovation stage is important in explaining vertical integration. They find that R&D-intensive firms that are at an early stage of unrealized innovation are less likely to become targets of vertical acquisitions[10].

[9] Dasgupta and Stiglitz (1980) suggest that more competition reduces the monopoly rents that reward successful innovators, hence innovation should decline with competition.

[10] They further note: "When innovative assets require further investment and development, it is optimal to leave control to the firms that perform the innovation, as their incentives are most important for the value of the vertical relationship (e.g., Aghion and Tirole 1994), and because their employees may leave in case of acquisition and take the unrealized innovation (i.e., their ideas) with them (e.g., Hart and Moore 1994)." See, e.g., a seminal case on inevitable disclosure of trade secrets of a former employee in

However, if innovation is patented, i.e., realized, and thus legally protected, incentives to innovate decline and incentives to commercialize the innovation increases in importance. Another related paper in this field is the one of Bena and Li (2014), who conclude that synergies obtained from combining innovation capabilities are important drivers of acquisitions. Their results show that, after looking at a unique patent-merger data set, companies with large patent portfolios and low R&D expenses are acquirers, while companies with high R&D expenses and slow growth in patent output are targets. I build on one of their findings – namely that technological overlap between firms' innovation activities has a positive and significant effect on the likelihood of merger pair formation – by demonstrating that the relation between target's intellectual property value and the size of the BTF is increasing in the degree of technological proximity between the merging firms.

The industry-level instrumental variable I suggest in this paper can be used by researchers to mitigate endogeneity concerns, especially if applied in cases where the variable of interest is related to firm-level (R&D-)intangibles, as in Ewens, Peters, and Wang (2020). They characterize off-balance sheet intangibles – knowledge (R&D) and organizational (SG&A) capital – by using real transaction prices paid in M&A deals. The core of their contribution is the exploitation of market valuations of acquired intangible assets[11]: they validate and update parameter estimates for (1) the depreciation parameters for knowledge capital based on prior R&D spending and (2) the fraction of SG&A capital that represents investment into long-lived organizational capital. I apply their capitalization model to estimate the component of intellectual property in target firms' market values. This component is expressed by their accumulated and depreciated knowledge and organizational capital stocks scaled by market capitalization, representing my main variable of interest.

PepsiCo, Inc., v. Redmond – 54 F.3d 1262 (1995), available online on LexisNexis: https://www.lexisnexis.com/community/casebrief/p/casebrief-pepsico-inc-v-redmond (permanent link).

[11] Extending their parameter estimates to all publicly listed firms requires that the prices paid for intangible capital in their sample represent a public or market value. Given that prices paid for targets in acquisitions contain private valuations of the acquirer about the intended firm pair combination, the authors properly adjust acquisition prices for over-/underpayment and synergies, and adjust goodwill (using information obtained through purchase price allocations in acquirers' subsequent SEC documents, such as 10-Ks, 10-Qs, 8-Ks, and S-4s).

Besides, another contribution of this paper is to explain drivers of implementing BTFs in merger agreements as well as drivers of BTFs' relative size, which arise from a legal, regulatory perspective. If mergers are horizontal and/or are thought to significantly alter product market competition by increasing the market power of the combined firm beyond certain limits, the deal stands under augmented scrutiny by regulating (antitrust) authorities. I apply the merger-induced same-industry concentration increase[12] as introduced in Gao, Peng, and Strong (2017) and suggested by the U.S. Department of Justice and the Federal Trade Commission (2010). This "regulatory risk" measure proves to be a significant determinant of both the probability of BTF inclusion and BTF size, and complements the empirical findings related to BTF pricing in Chen et al. (2020b). They further find that both the likelihood of inclusion and the size of the BTF increase in the volatility of target's value to the bidder and with the expected completion time of the takeover. Chen et al. (2020b) note that acquirers cannot easily walk away from an announced deal if no BTF was agreed on, yet exogenous reasons under acquirer's sphere of responsibility or target material adverse changes can still force both parties to abandon the transaction. My findings are also consistent with Choi and Wickelgren's (2019) paper[13], who show theoretically that BTFs act as a commitment device for acquirers.

A direct managerial implication of this paper is that implementing BTFs in M&A contracts serve as a mechanism that provide target firms compensation for revelation of information in M&A negotiations if acquirers terminate deals. BTFs thereby increase targets' incentives to reveal information and increase acquirers' incentives to close the deal.

This paper proceeds as follows. In Section 2, I develop my hypotheses. I provide a sample overview, describe the empirical methodology and key variables in Section 3. I present the main regression results and relations between intellectual property protection and technological proximity as well as product market rivalry in Section 4. In Section 5, I provide additional robustness and subsample tests to strengthen my reasoning. Section 6 concludes.

[12] Defined as the merger-induced change (increase) in industry sales concentration in the same SIC4-industry, whereas I measure industry sales concentration as the Herfindahl-Hirschman Index (HHI), i.e., based on firms' sales (market shares) at the last fiscal year-end date prior to deal announcement.
[13] They are – to my knowledge – the first to analyze bidder termination fees using game theory.

2 Theoretical Reasoning, Hypothesis Development, and Predictions

In this paper, I apply Ewens' et al. (2020) parameter estimates for knowledge and organizational capital stocks, obtained through their novel approach by exploiting acquisition prices paid for intangible assets of M&A targets, to proxy for the share of target firm's intellectual property value in its market valuation. I then relate this ratio to an outcome of the private deal negotiation process, namely the size of the negotiated bidder termination fee (BTF). I show that the higher this value ratio, the higher the BTF (also scaled by target firm's size), which compensates the target with a payment by the acquirer if the latter terminates the deal due to reasons under his control (and walks away with revealed sensitive private information, such as business and trade secrets, among many others). This information revelation represents – sometimes existential – indirect costs incurred by the target in failed M&A negotiations.

As Ewens et al. (2020) highlight in their paper, current accounting standards dictate R&D and SG&A expenditures to be fully expended in the period they occur, and prohibit the disclosure of internally generated intangible capital on firms' balance sheets. These off-balance sheet intangibles – most of all knowledge and organizational capital based on R&D and SG&A expenditures – have become increasingly important over the last few decades. Scholars and GAAP's accounting standards frequently quote their lack of collateral value, the risks associated with estimating their useful life, and uncertainty in measuring their value[14] for the main reasons why R&D and SG&A expenditures cannot be capitalized on the firm's balance sheet[15]. However, these intangible assets are among the most important sources enabling long-term economic growth through innovation. Their lack of capitalization thus results in a downward bias of reported assets, which is one of the main reasons why market-to-book ratios seem to inflate over recent decades[16].

[14] https://asc.fasb.org/section&trid=2127268#topic-730-10-05-subsect-01-108369 (requested: 03/21/2020).

[15] For an intangible asset to be capitalized, i.e., to be identifiable, ASC 805 requires the asset under consideration to meet either the separability criterion (meaning it can be separated from the entity and sold) or the contractual-legal criterion (meaning that the control of future economic benefits arising from the asset is warranted by contractual or legal rights). This is the case for, e.g., computer software. See Ewens et al. (2020) for a detailed discussion of intangible accounting.

[16] See Figure A4 in the Appendix with plots documenting the trend in market-to-book ratios over time, based on estimates obtained in Ewens et al. (2020).

On the other hand, once successfully acquired, intangible assets of the target are recorded as either goodwill (GW) or identifiable intangible assets (IIA) on acquirer's balance sheet. I.e., the acquirer pays for the target the following purchase price[17]:

$$Acq\ Price\ Paid\ for\ Tgt \ = \ P_{Tgt\ Physical\ Assets} \ + \ P_{Tgt\ Financial\ Assets} \ + \ P_{Tgt\ GW} \ + \ P_{Tgt\ IIA} \ + \ P_{Tgt\ UIA}$$

where the index $_{Tgt\ UIA}$ stands for target's unidentifiable intangible assets. On target i's side, its intangible capital can be separated into externally acquired intangible capital, $I_{i,t}^{ext}$, disclosed on its balance sheet in year t, and internally generated intangible capital $K_{i,t}^{int}$:

$$Tgt\ Total\ Intangible\ Capital_{i,t} \ = \ I_{i,t}^{ext} \ + \ K_{i,t}^{int}$$

whereas $K_{i,t}^{int}$ can be separated into knowledge $(G_{i,t})$ and organizational capital $(S_{i,t})$[18]:

$$K_{i,t}^{int} \ = \ G_{i,t} \ + \ S_{i,t}$$

with knowledge capital stock value defined as accumulated and depreciated R&D expenses using the perpetual inventory method, with industry-specific depreciation factor δ_G:

$$G_{i,t} \ = \ (1 - \delta_G)\, G_{i,t-1} \ + \ R\&D_{i,t}$$

and organizational capital stock value defined as accumulated and depreciated SG&A expenses, also applying the perpetual inventory method, with industry-specific fraction γ representing the share of SG&A invested into long-living organizational capital, and depreciation factor δ_S:

$$S_{i,t} \ = \ (1 - \delta_S) S_{i,t-1} \ + \ \gamma\ SG\&A_{i,t}$$

Due to data limitations, especially if the target was not publicly listed before, I calculate the value of intangible capital stocks over the last ten years prior to deal announcement, resulting in the following capitalization model:

$$K_{i,t}^{int} \ = \ \sum_{k=1}^{10} (1 - \delta_G)^k\ R\&D_{i,t-k} \ + \ \sum_{k=1}^{10} (1 - \delta_S)^k\ \gamma\ SG\&A_{i,t-k}$$

[17] Including a control premium.

[18] As modeled in Ewens et al. (2020), who build on a large empirical literature (e.g., Eisfeldt and Papanikolaou (2013), Peters and Taylor (2017), and Falato, Kadyrzhanova, Sim, and Steri (2020)).

As for physical assets, Ewens et al. (2020) estimate depreciation parameters δ_G for knowledge capital stocks based on prior R&D spending, as well as the share γ of SG&A capital that represents investment into long-lived organizational capital, using the value of 0.2 as the literature's consensus estimate for δ_S. To obtain a measure that is comparable across firms and not diluted with private synergy and over-/underpayment, the final step in creating the value ratio is to relate both capital stock measures to target firm's market value, i.e., market capitalization two months prior to deal announcement[19].

Reasons why BTFs are negotiated and included in merger agreements typically include concerns threatening deal closure under acquirer's area of control as well as exogenous reasons. First, the bidder may fail to obtain (debt) financing and/or fail to obtain shareholder approval. The latter could happen if the deal is planned to be paid with newly issued acquirer stock and the new stock issue exceeds 20% of prior shares outstanding. Second, a breach of representations, warranties and/or covenants by the bidder might occur which triggers the payment of a BTF. Third, a fee can be implemented to terminate the deal if the acquirer fails to close before an ex-ante determined "drop dead date". Fourth, an exogenous reason for termination and under acquirer's responsibility is the failure to obtain regulatory approval by the Department of Justice Antitrust Division (DoJ) or the Federal Trade Commission (FTC). Fifth – although very rarely – a competing bid with the primary bidder as the target firm ("bid-for-bidder") may arise, and sixth, the exercise of a pure termination option by the bidder (Chen et al. (2020b), Afsharipour (2010), and Quinn (2010)).

2.1 Target Firm's Intellectual Property Value and Bidder Termination Fees

Ample research emphasizes that satisfying acquirers' innovation needs can be achieved by selecting successfully innovating targets, leveraging innovation synergies, and realizing gains through the commercialization of targets' intellectual property (e.g., Frésard et al. (2020), Phillips and Zhdanov (2013), and Bena and Li (2014)). This intellectual property is sometimes the most important asset a firm has, and some firms might exist only because of one specific

[19] I use market capitalization since asset prices are forward looking. As shown in Section 5, my results are robust to other scaling variables, such as deal value and, in untabulated regressions, also total assets (whereas this would be a problematic scaling variable, given that book values do not – as outlined above – appropriately capture the (full) value of intangibles, and especially the intangibles considered here).

idea. A direct implication is that, for the good of society through enabling growth by incentivizing investment in innovation, legislation's duties should entail the protection of it. This is warranted through, e.g., granted patents, copyrights, trademarks, and trade secret law. On an employee-level[20], firms can rely on legal protections such as non-disclosure agreements (NDAs) and non-compete clauses in employment contracts, though they may be time limited.

In merger negotiations, however, bidders gather significant private information about the target's (future) business, its methods and techniques for manufacturing and processes, as well as other technological competitive advantages, *without* the target being protected by above mentioned legally enforcable rules[21]. I assume that the target has full control over the amount and granularity of revealed information, as well as the timing of its disclosure to the bidder. E.g., the target usually provides potential acquirers a data room and the latter conduct various forms of due diligences. These information are important to determine the acquisition price including the deal premium, and to assess post-merger integration, which is vital for merger success (Hoberg and Phillips (2019)). The target has an incentive to disclose certain private information to the acquirer, resulting in an increase of its bargaining power, and could thereby increase the odds of receiving a higher takeover premium, which is beneficial for its shareholders, all else equal. I further expect the target to reveal the most sensitive information not to all potential bidders, but only to the final acquirer once the merger agreement is signed and the bidder termination fee is set. As put forward in the introduction, the revelation of sensitive private information to the acquirer is not a first-order problem if deals are closed successfully, but if deals ultimately fail.

Although there exists no legally defined trigger in bidder termination fee provisions to induce a "sensitive information revelation payment" to the target by the acquirer if the latter abandons the deal, this paper investigates whether there is a substantial fraction priced into the BTF that reflects this indirect cost component not protected by other law.

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[20] For literature related to employee mobility and protection of trade secrets, see, e.g., Klasa et al. (2018), Glaeser (2018), Contigiani, Hsu, and Barankay (2018), and Chen, Gao, and Ma (2020a).

[21] It is common in almost every transaction to sign a non-disclosure agreement (NDA) already well before signing the binding merger agreement, but it is the merger agreement that contains the negotiated BTF. Confidentiality agreements (or non-disclosure agreements) do not provide a compensatory payment to the target if the deal is abandoned by the acquirer. Therefore, these agreements are then worthless.

Since it is difficult – if not impossible – to directly quantify target firm's (private) value of its intellectual property[22], I apply the model above to create a proxy that I claim is highly correlated with this value: the value of target firm's knowledge capital stock based on accumulated and depreciated R&D expenses[23]. As in Ewens et al. (2020), I also calculate each firms' organizational capital stock based on SG&A expenses as described above and scale both capital stock values by target firm's market capitalization 42 trading days prior to offer announcement to enable comparison among deal-level observations. Thus, I obtain two measures: R&D stock value per unit of target firm's value, and SG&A stock value per unit of target firm's value. Theory (e.g., Eisfeldt and Papanikolaou (2013, 2014), and Jovanovic (1979)) has argued that organizational capital is bound to the organization itself and to key employees, thus its efficiency is firm-specific and hard to transfer via mergers. Recent empirical literature (e.g., Li, Li, Wang, and Zhang (2018)) finds that acquirers benefit more when target firms have higher organizational capital, suggesting that it is transferable via mergers. Yet, despite the literature's controversial argumentation, I assume that organizational capital has little "secrecy" value outside the originating firm. Thus, I expect only target firm's knowledge capital stock to be correlated with both inclusion and size of the bidder termination fee. The central hypothesis of this paper hence is:

Hypothesis 1: *The higher the value of target firm's knowledge capital stock, the higher the negotiated bidder termination fee.*

[22] Including all trade secrets, not yet patented innovation, other business as well as technology secrets, and "negative" information as mentioned in the introduction.

[23] In Table 9 and in Figure A2 in the Appendix, I show – similar to Ewens et al. (2020) – that target knowledge capital stock is a highly significant predictor of both the market value and the scientific value of target's patents, as well as the number of patents granted to the target in the year prior to deal announcement (using data obtained from Kogan et al. (2017)), and total patent stock (all patents that are not yet expired at the last fiscal year-end date prior to deal announcement, calculated using patent data obtained from the University of Virginia (UVA) Darden Global Corporate Patent Dataset, see Bena, Ferreira, Matos, and Pires (2017)). All explanatory variables are lagged, logged and scaled by total assets. Beyond that, in regressions in Table 10, I show, similar to Glaeser (2018), that R&D intensity, measured with my proposed value ratio based on market values, is a reliable and highly statistically significant predictor of both using the word "trade secret", "trade secrets" and/or "trade secrecy" in target's 10-K filing prior to offer announcement, as well as the frequency, i.e., how often the word combinations are mentioned. In both regressions the coefficient is positive and statistically highly significant. Figure A3 in the Appendix shows the respective plot of associated predicted probabilities.

2.2 Short-Term Target Firm Value Effects around Deal Resolution

If announced deals are terminated, one central stylized fact is that targets' share prices plummet. The reason behind this is that target firm's shareholders then don't receive the usually significantly positive control premium offered by the acquirer (e.g., documented in the comprehensive survey of Betton, Eckbo, and Thorburn (2008)). However, the negative stock price reaction might differ with the method of payment offered by the acquirer, as cash bids have been found to reveal prior undervaluation of the target: these bids revalue target's market value at deal failure by approximately +15% compared to pre-announcement levels (Malmendier, Opp, and Saidi (2016)).

If the reason of deal termination falls under the acquirer's sphere of control and triggers the payment of a bidder termination fee, I expect, all else equal, a less negative target stock price reaction on the deal termination date[24], given that the cash fee is beneficial for the target. This leads to the second hypothesis:

Hypothesis 2: *If the acquirer cancels the deal and the higher the bidder termination fee, the higher target firm's cumulative abnormal deal resolution returns.*

2.3 Interaction between Intellectual Property Protection and Technological Proximity

Innovation needs of acquirers are best satisfied by selecting successfully innovating targets, leveraging the firm's combined innovation synergies, and realizing gains through the commercialization of the merged firm's intellectual property (e.g., Frésard et al. (2020), Phillips and Zhdanov (2013), and Bena and Li (2014)). A successful post-merger integration and realization of synergies is likely, if the acquirer is well integrated and selects a target complementary to his own products and research activities (Hoberg and Phillips (2019)).

Building on their findings as well as the results of Phillips and Zhdanov (2013), I suggest that my proposed relation between target firm's knowledge capital stock value and the size of

[24] Compared to the base case where the acquirer abandons the deal without any negotiated BTF and thus leaves the target as "damaged goods".

the negotiated BTF increases in the degree of both firms' technological proximity. The economic intuition is that the more technologically close the firm pair's knowledge base is, the more likely the fit of the target for acquirer's innovation needs and the ex-post realization of synergies. Furthermore, I claim that intellectual property is easier to ascertain for close technology rivals than for firms totally unrelated in their respective technology space. Thus, building on hypothesis 1, I formulate hypothesis 3a:

Hypothesis 3a: *The higher the degree of technological proximity between acquirer and target, the more pronounced the relation between target firm's knowledge capital stock value and the size of the negotiated bidder termination fee.*

2.4 Interaction between Intellectual Property Protection and Product Market Rivalry

Firms that operate in similar product markets are usually their strongest competitors and could gain the highest advantage from utilizing each other's sensitive private technology and business knowledge. Yet, on the other side, acquirers may have less incentives in exploiting targets' intellectual property if their product markets are completely unrelated to each other. I assert that the proposed relation between target firm's knowledge capital stock value and the size of the negotiated BTF should increase in the degree of both firms' product market rivalry. The economic rationale is that the more likely both firms are product market rivals, the more likely can the acquirer derive the highest economic future value from exploiting target's intellectual property. I.e., secrecy might be highly valuable for both firms, but the relation should be stronger if they are direct competitors. Hence, hypothesis 3b finally states:

Hypothesis 3b: *The higher the degree of product market rivalry between acquirer and target, the more pronounced the relation between target firm's knowledge capital stock value and the size of the negotiated bidder termination fee.*

3 Sample Overview, Methodology, and Key Variables

3.1 Sample Overview

To form the M&A sample, I begin by screening all transactions from Standard & Poor's Capital IQ database announced between January 01, 2004 and December 31, 2017[25]. I apply the following filters commonly used in the literature: first, I select all M&A deals that are also either completed or withdrawn in the respective period. Second, I identify all M&A transactions in which the acquirer and the target are both publicly listed U.S. firms[26], the acquirer holds less than 50% of target's outstanding shares prior to offer announcement, and aims for a change in control in the target firm (i.e., the acquirer must seek a majority stake). Third, I require the deal value, i.e., the total transaction value excluding assumed liabilities, to exceed USD 1 million to eliminate the many small and economically less significant transactions. Fourth, since I need the most accurate data on negotiated bidder and target termination fees, I require every transaction-target to have valid merger documents filed with the Securities and Exchange Commission (SEC) at or shortly after the deal announcement date[27]. Fifth, to proxy for the extent to which the target firm has produced (secret) intellectual property, I further restrict the sample to transactions in which the target has valid data on past R&D or SG&A spending[28]. These filters result in a final data sample of 769 unique transactions[29].

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[25] I focus on this sample period, since sophisticated trade secret law (mainly the Uniform Trade Secret Act (UTSA) and the inevitable disclosure doctrine (IDD)) has been widely adopted in all U.S. states after 2004 (except Texas (2013), New Jersey (2012), and Wyoming (2006)). Moreover, this is unlikely to negatively affect my results, given that these staggered passages of both the UTSA and IDD are a shock to trade secrecy on an employee-firm-level. This likely positively affects merger incidence justified by information expropriation, because the UTSA and IDD exogenously decreased knowledge-worker mobility. See, e.g., Dey and White (2019), Klasa et al. (2018), Contigiani et al. (2018), and Glaeser (2018).

[26] This is to ensure that SEC EDGAR merger filings are available from which I retrieve data on the exact BTF and the selling method (auction vs. negotiation) in the respective background section.

[27] I manually retrieve the SEC EDGAR filings for the respective transaction since some papers argue that termination fee data in both Standard & Poor's Capital IQ and Refinitiv's SDC Platinum are not convincingly reliable prior to 2007.

[28] Valid data in this case means that I also include all observations in which there is at least one non-missing (i.e., at least one "0" or another positive value) data point on target firm's R&D or SG&A expenses in Compustat in the last ten years prior to offer announcement. I do this in order to avoid sample selection. The results are robust and remain unchanged to including a "missing R&D" dummy.

[29] Table A2 in the Appendix lists the detailed sample selection process with the number of remaining observations after applying respective filters. I obtain qualitatively and quantitatively similar results if

3.2 Methodology and Key Variables

The baseline specification to measure the effect of target firm's intellectual property value on the size of the negotiated bidder termination fee is the following linear fixed effects regression model:

$$
\begin{aligned}
BTF\ Size_{i,t} = \ & \alpha_{i,t} + \beta_1\ Tgt\ Know\ Cap\ Stock_{i,t} + \beta_2\ Tgt\ Org\ Cap\ Stock_{i,t} \\
& + \beta_3\ Tgt\ Total\ Intangibles\ Ratio_{i,t-22} + \beta_4\ Tgt\ Tangibility_{i,t-22} \\
& + \beta_5\ Tgt\ Market\text{-}to\text{-}Book_{i,t-22} + \beta_6\ TTF\ Size_{i,t} \\
& + \eta\ Deal\ Characteristics_{i,t} + \theta\ Acq\ Firm\ Characteristics_{i,t} \\
& + \varphi\ Acq\ Industry \times\ Year\ FE_{i,t} + \vartheta\ Tgt\ Industry\ FE_{i,t} + \varepsilon_{i,t}
\end{aligned}
$$

where i indexes the transaction (i.e., the unique acquirer-target-combination), t indexes the time (i.e., announcement date of the transaction), α is an intercept, and β_1 is the coefficient of primary interest – the estimate of the effect of target firm's intellectual property value on the size of the bidder termination fee. The dependent variable is the dollar value of the negotiated bidder termination fee scaled by target firm's market capitalization 42 trading days (i.e., two calendar months) prior to offer announcement. This scaling makes the dependent variable comparable across transactions and captures the potential economic impact on target firm's value should the deal be terminated and triggering a bidder termination fee payment by the acquirer to the target.

Intangible Capital Stock Measures

The main variable of interest in this paper is *Tgt Know Cap Stock*, the proxy for the value of target firm's intellectual property not yet protected by patents and other law. Applying Ewens' et al. (2020) model for intangible capital stocks, *Tgt Know Cap Stock* is defined as accumulated and depreciated (depreciation factor δ_G) R&D expenses over the last ten years prior to offer announcement, also scaled by target firm's market capitalization 42 trading days

I further restrict the sample to excluding both acquirers and targets from the financial sector (SIC codes 6000–6999) as well as utilities (SIC codes 4900–4999).

(two calender months) prior to offer announcement, to ensure that target's stock prices do not reflect run-up movements of the upcoming bid:

$$Tgt\ Know\ Cap\ Stock_{i,t} = \frac{\sum_{k=1}^{10}(1-\delta_G)^k\ R\&D_{i,t-k}}{Tgt\ Market\ Capitalization_{i,t-42}}$$

Tgt Org Cap Stock is defined likewise, it is equal to the accumulated and depreciated (depreciation factor δ_S) SG&A expenses over the last ten years prior to offer announcement, scaled by target firm's market capitalization 42 trading days prior to offer announcement, where γ represents the share of SG&A expenses invested into long-lived organizational capital:

$$Tgt\ Org\ Cap\ Stock_{i,t} = \frac{\sum_{k=1}^{10}(1-\delta_S)^k\ \gamma\ SG\&A_{i,t-k}}{Tgt\ Market\ Capitalization_{i,t-42}}$$

Other Controls

Tgt Total Intangibles Ratio is the sum of accumulated goodwill and identifiable intangibles[30] from its balance sheet, divided by total assets and obtained 22 trading days prior to deal announcement. *Tgt Tangibility* is net property, plant, and equipment of the target, also scaled by total assets 22 days prior, and controls for target's physical asset intensity. *TTF Size* is – similar to the dependent variable *BTF size* – the dollar value of the negotiated target termination fee scaled by target firm's market capitalization 42 trading days prior to offer announcement. It is important to also control for *TTF Size*, because the TTF is also determined at the end of the private deal negotiation yet comprises legally and economically different triggers[31]. These controls are included to reduce omitted variable bias, because the causal interpretation of the variable of interest should be independent of the structure of target's assets.

Key *Deal Characteristics* variables include, among common M&A controls: *Tgt Initiation*, a dummy variable variable that equals 1 if the target initiated the deal, and 0 otherwise, and is included after considering Masulis and Simsir (2018), who find that targets initiate deals

[30] I.e., those intangible assets that can be separated from other assets and even be sold, such as, e.g., patents, patent licenses, copyrights, trademarks, trade names, and service marks.

[31] It is important to note that the BTF is not a symmetrical response to the TTF from a legal perspective. TTFs are negotiated to compensate the acquirer for out-of-pocket expenses in case the target terminates the deal due to, e.g., receiving and accepting a third-party bid or not obtaining shareholder approval.

motivated by their economic weakness and financial constraints. Under these circumstances, a significant amount of bargaining power is shifted to the acquirer and systematically lowers the odds in persuading him to provide a BTF, all else equal. *Deal Value* is the USD (bn) value of the transaction, i.e., total transaction value excluding assumed liabilities. *Cash Only* is a dummy variable that equals 1 if the payment by the acquirer is made entirely in cash, and 0 otherwise. It is well documented in the literature (e.g., Betton et al. (2008)) that cash deals are usually smaller, i.e., have smaller deal values, and cluster around high relative sizes of the firms involved, meaning that the acquirer is usually much bigger than the target in cash deals. Similar to the economic intuition for target-initiated deals, this creates a natural bargaining power imbalance where one would expect to less likely observe BTFs (in pure cash deals). *Tender Offer* is a dummy variable that equals 1 if the deal is classified as a tender offer, and 0 otherwise. Tender offers are characterized by the acquirer often circumventing target firm's management and directly submitting a takeover bid to target's shareholders. I thus propose that, due to the lack of a direct negotiation between the firms, a BTF is significantly less likely in tender offers, on average. *Post Closing Highly Conc Industry* is a dummy variable that equals 1 if the planned deal results in the SIC4 industry Herfindahl-Hirschman Index (Post Closing Industry HHI) exceeding 0.25, and 0 otherwise. The U.S. Department of Justice (DoJ) and the Federal Trade Commission (FTC) define in their 2010 horizontal merger guidelines an industry as a highly concentrated market if the HHI increases beyond 0.25. Given that proposed deals that would result in a highly concentrated market receive heightened attention from those regulating (antitrust) authorities, I expect a BTF to be more likely included in such deals[32]. *Acq (Tgt) All Financial Advisor Fees* $_{\textit{Deal Value}}$, respectively, is the imputed USD (mm) value of acquirer (target) financial advisor fees irrespective of the deal outcome, i.e., directly assignable out-of-pocket expenses, scaled by *Deal Value*. These advisor fees are sunk cost if deals are terminated and are thus expected to be correlated with both BTF and TTF. Lastly, I control for variables capturing acquirer's bargaining power, financial constraints, and uncertainty over its value. Especially concerns of acquirer's financial soundness are reasons why the acquirer is swayed to provide a BTF. Besides market capitalization, stock return volatility, and market leverage, I include *Acq Dividend Payer*, a dummy variable that equals 1 if the acquiring firm

[32] Included as a proxy for ex-ante regulatory risk.

paid positive dividends[33] during the fiscal year preceding the offer announcement, and 0 otherwise. The intuition for including the dividend payer dummy is, that if the acquirer did pay any dividends during the fiscal year prior to deal announcement, he might not be financially constrained, thus has a lower risk of obtaining financing, hence a BTF should be less likely[34].

I also include *Acquirer Industry* × *Year Fixed Effects* and *Target Industry Fixed Effects*, based on the first digit of the Standard Industrial Classification (SIC) code and the year of deal announcement (e.g., Betton et al. (2008), Malmendier et al. (2016)) to control for aggregate shocks to takeover activity in certain industries and across years, and further unobserved heterogeneity (Gormley and Matsa (2014)). All variables are additionally defined in Table A1 in the Appendix.

4 Empirical Results

4.1 Key Descriptive Statistics

Table 1 presents summary statistics for the U.S. M&A sample including transactions announced between 2004 and 2017. The mean of *BTF Dummy* is 0.293, suggesting that about 29% of merger agreements include a negotiated bidder termination fee provision. To the contrary, about 97% of transactions are equipped with a target termination fee provision. These values are consistent with the literature, as similar values are obtained in, e.g., Chen et al. (2020b), yet databases are known to underreport their incidence, specifically prior to 2007. The dollar value range for the bidder termination fee peaks in values in the low billions, with the maximum value of USD 3.5 billion paid by the acquirer, Halliburton Company, to the target, Baker Hughes, Inc., for the failed deal in 2016. *BTF Size* (the main dependent variable) and *TTF Size* are the respective dollar values scaled by target firm's market capitalization and average in values of around 1.8% and 5.1%, with maximum values exceeding 43% and 34%, respectively. This emphasizes their economic significance and value effects for the target if

[33] On either common and/or preferred stock.

[34] In additional regressions, I also include commonly known measures of financial constraints for the acquiring firm, such as the indices developed in Hadlock and Pierce (2010) (*SA-Index*), Whited and Wu (2006) (*WW-Index*), and Kaplan and Zingales (1997) (*KZ-Index*).

deals are terminated and fees are paid. The median of *Tgt Know Cap Stock* is zero, suggesting that most of the firms do not invest in R&D, consistent with prior findings as in, e.g., Glaeser (2018), and Bena and Li (2014). Yet, on average, target firm's knowledge capital stock represents about 13% of its total market value. The average value for *Tgt Org Cap Stock* is 35.7%, and maximum values are smaller than maximum values for *Tgt Know Cap Stock*, which peak in values exceeding ten times its market valuations[35]. This suggests a high significance of R&D investments for a substantial number of firms. Since deal values usually exceed market valuations, the ratios for *Tgt Know Cap Stock* $_{\textit{Deal Value}}$ and *Tgt Org Cap Stock* $_{\textit{Deal Value}}$ are somewhat smaller. Deal values average in the low billions, with a median value of USD 441 million.

Table 1

Summary Statistics

Table 1 reports summary statistics of the sample consisting of 769 U.S. M&A transactions announced between January 01, 2004 and December 31, 2017. Number indices display the point in time (i.e., trading day) relative to the offer announcement (OA) date when the variable was measured. Letter indices refer to the variable the non-indexed variable is scaled with, i.e., *BTF Size* $_{\textit{Deal Value}}$ is the USD amount of the bidder termination fee scaled (divided) by the USD amount of *Deal Value*. Cumulative abnormal returns (*CAR*) are measured in symmetric event windows around deal resolution, applying a Carhart (1997) four-factor model (*C4*) to model normal returns, respectively. All variables that are not indexed, i.e., capital stock data (*Cap Stock*), other accounting data, proximity and similarity measures, measures of financial constraints, patent data, and *Tgt SIC2 Industry R&D Worker Ratio*, are measured on the last fiscal year end date (or quarter year end, if available) prior to offer announcement. All CARs, Market-to-Book ratios, and *Relative Size Market Cap* $_{[OA-22]}$ are winsorized at the 1st and 99th percentile. All variables are defined in detail in Table A1 in the Appendix.

	Summary Statistics					
Variables	Obs.	Mean	Median	Std. Dev.	Min.	Max.
Panel A: Termination Fees and Target Intangible Capital Stocks						
BTF Dummy	769	0.293	0	0.455	0	1
TTF Dummy	769	0.970	1	0.170	0	1
BTF $_{\text{Dollar Value}}$	769	45.805	0.000	213.445	0.000	3,500.000
TTF $_{\text{Dollar Value}}$	769	75.857	13.000	202.684	0.000	1,920.000
BTF Size	769	1.729	0.000	3.539	0.000	43.184
TTF Size	769	5.069	4.778	2.538	0.000	34.049
BTF Size $_{\text{Deal Value}}$	769	1.228	0.000	2.465	0.000	30.214
TTF Size $_{\text{Deal Value}}$	769	3.398	3.387	1.539	0.000	30.171
Tgt Know Cap Stock $_{\text{Dollar Value}}$	769	74.311	0.000	428.790	0.000	10,856.900
Tgt Org Cap Stock $_{\text{Dollar Value}}$	769	302.094	46.494	1,199.158	0.000	19,291.560

[35] This extremely research intense target was Icoria, Inc., a pharma/biotech company founded in 1997 that discovers and develops multiparameter biomarkers which enable developing multianalyte diagnostics used to define and grade pathology or disease states. The firm was successfully acquired by Clinical Data, Inc., on December 20, 2005.

Tgt Know Cap Stock	769	0.131	0.000	0.546	0.000	10.074
Tgt Org Cap Stock	769	0.357	0.172	0.677	0.000	8.478
Tgt Know Cap Stock $_{\text{Deal Value}}$	769	0.079	0.000	0.290	0.000	4.553
Tgt Org Cap Stock $_{\text{Deal Value}}$	769	0.231	0.121	0.388	0.000	4.274
Tgt 5YR Avrg Yearly Know Cap Growth	324	13.836	10.474	20.655	−40.494	97.176
Tgt Know Cap Intensity	697	0.184	0.000	0.264	0.000	1.000
Panel B: Deal and Industry Characteristics, and Measures of Technological Proximity and Product Market Rivalry						
Tgt Initiation	769	0.322	0	0.468	0	1
Auction	769	0.599	1	0.490	0	1
Deal Value	769	2.657	0.441	6.943	0.010	79.406
Friendly	769	0.996	1	0.062	0	1
Cash Only	769	0.395	0	0.489	0	1
Tender Offer	769	0.156	0	0.363	0	1
Horizontal Takeover	769	0.489	0	0.500	0	1
Relative Size Market Cap $_{[\text{OA–22}]}$	769	40.003	6.576	157.483	0.333	1,792.928
Post Closing Industry HHI	769	0.168	0.118	0.162	0.010	0.995
Post Closing Industry HHI Increase	769	0.011	0.001	0.042	0.000	0.493
Post Closing Highly Conc Industry	769	0.055	0	0.227	0	1
Acq All Financial Advisor Fees $_{\text{Dollar Value}}$	769	7.584	3.515	9.613	0.029	60.000
Tgt All Financial Advisor Fees $_{\text{Dollar Value}}$	769	10.161	4.300	13.468	0.015	94.700
Acq All Financial Advisor Fees $_{\text{Deal Value}}$	769	0.970	0.773	0.801	0.001	9.998
Tgt All Financial Advisor Fees $_{\text{Deal Value}}$	769	1.114	0.997	1.111	0.001	13.026
Technological Proximity (Tech Prox)	233	0.155	0.154	0.096	0.012	0.520
Product Market Similarity (PMS) $_{\text{TNIC1}}$	694	0.190	0.174	0.116	0.000	0.928
Product Market Similarity (PMS) $_{\text{TNIC2}}$	603	0.131	0.114	0.109	0.000	0.848
Product Market Similarity (PMS) $_{\text{TNIC3}}$	525	0.111	0.088	0.108	0.000	0.811
Acq Induced Cancellation	769	0.017	0	0.129	0	1
Third Party Competing Bid Cancellation	769	0.008	0	0.088	0	1
Deal Completion	769	0.950	1	0.217	0	1
Kick-Off vs. AD	398	4.004	3.567	2.254	0.300	12.867
First Board Meeting vs. AD	398	3.672	3.167	2.322	0.167	12.800
Confidentiality Agreement vs. AD	398	3.262	2.500	2.802	0.067	18.200
Kick-Off vs. RD	398	9.859	9.400	3.779	2.467	30.167
First Board Meeting vs. RD	398	9.527	8.767	3.958	2.000	30.033
Confidentiality Agreement vs. RD	398	9.116	8.267	4.098	2.300	28.267
Any Pre-Contact with Acq	398	0.384	0	0.487	0	1
Panel C: Acquiring Firm Characteristics						
Acq Market Cap $_{[\text{OA–22}]}$	769	19.293	2.338	46.473	0.014	461.758
Acq Market-to-Book $_{[\text{OA–22}]}$	769	3.454	2.121	5.965	0.429	76.642
Acq 1YR Stock Return Volatility $_{[\text{OA–1}]}$	769	30.303	26.669	15.389	10.401	122.573
ln Acq 1YR Stock Return Volatility $_{[\text{OA–1}]}$	769	3.311	3.283	0.432	2.342	4.809
Acq Market Leverage $_{[\text{OA–22}]}$	769	0.139	0.109	0.131	0.000	0.927
Acq Dividend Payer	769	0.671	1	0.470	0	1
Acq Hadlock-Pierce-Index	751	−4.265	−4.546	0.488	−4.637	−2.228
Acq Whited-Wu-Index	697	0.534	0.369	1.431	−8.594	6.356
Acq Kaplan-Zingales-Index	632	−9.021	−4.841	11.203	−56.194	3.094

Panel D: Target Firm Characteristics						
Tgt Market Cap [OA–42]	769	1,960.597	301.480	5,411.878	5.262	62,359.610
Tgt Market-to-Book [OA–22]	769	2.973	1.833	4.305	0.197	35.653
Tgt Total Assets [OA–22]	769	4,071.693	657.784	29,811.820	4.499	782,896.00
Tgt Total Intangibles [OA–22]	769	477.932	20.669	2,242.563	0.000	38,935.000
Tgt Goodwill [OA–22]	739	356.428	10.657	2,066.050	0.000	27,689.000
Tgt Identifiable Intangibles [OA–22]	729	127.606	3.500	649.848	0.000	10,453.000
Tgt Net PPE [OA–22]	769	575.996	24.304	2,252.972	0.000	31,281.000
Tgt Current Assets [OA–22]	513	682.084	189.113	1,482.475	3.680	14,712.000
Tgt Total Intangibles Ratio [OA–22]	769	0.136	0.039	0.187	0.000	0.832
Tgt Goodwill Ratio [OA–22]	739	0.096	0.020	0.141	0.000	0.721
Tgt Identifiable Intangibles Ratio [OA–22]	729	0.042	0.005	0.077	0.000	0.508
Tgt Tangibility [OA–22]	769	0.157	0.058	0.217	0.000	0.953
Tgt Current Assets Ratio [OA–22]	513	0.520	0.532	0.261	0.036	0.994
Tgt C4 CAR RD [−3;+3]	521	0.503	0.058	8.185	−47.611	128.883
Tgt Unique Product Industry	769	0.587	1	0.493	0	1
Tgt FF5 HTHC Industry	769	0.372	0	0.484	0	1
Tgt Patent Value (market-weighted)	190	411.059	20.288	2,058.386	0.199	22,597.090
Tgt Patent Value (citation-weighted)	190	43.398	9.455	118.632	1.000	1,224.381
Tgt Patent Count (recently granted)	190	15.911	4	46.098	1	508
Tgt Patent Count (total stock)	288	20.892	4	52.657	1	514
Tgt Trade Secrecy Mention Count in 10-K	751	1.775	0	2.845	0	27
Tgt SIC2 Industry R&D Worker Ratio	753	0.112	0.097	0.075	0.001	0.286
Tgt Firm Age	742	41.899	24	41.053	2	234

(Table 1 continued)

Approximately 60% of deals are classified as takeover auctions, i.e., transactions in which the private sales process is characterized by two or more prospective acquirers signing non-disclosure agreements with the target firm, nearly the same share as obtained in, e.g., Masulis and Simsir (2018) and Boone and Mulherin (2008). Approximately 16% of all deals are tender offers, and almost half of all deals are classified as horizontal takeovers, i.e., acquirer and target share the same SIC4 industry.

The mean value for *Post Closing Highly Conc Industry* is 5.5%, suggesting that every twentieth deal changes market composition in a way to likely receive extra scrutiny by regulating authorities. When it comes to the resolution of announced deals, nearly 95% of all deals are closed successfully within the sample period, whereas in about 2% of the cases the acquirer terminates the deal.

4.2 Baseline Regression Results: Target Firm's Intellectual Property Value and Bidder Termination Fees

According to hypothesis 1, targets with a high ratio of their knowledge capital stock to market value are assumed to be highly valuable because of their secret, private intellectual property. Acquirers aiming to satisfy their innovation needs could utilize this knowledge by purchasing these successfully innovating targets. Thus, the scaled size of the bidder termination fee, *BTF size*, is hypothesized to increase in *Tgt Know Cap Stock*, since the BTF is providing the target a compensation payment for revealing these private information to the acquirer if the latter abandons the deal. Hypothesis 1 hence predicts a positive relation between *Tgt Know Cap Stock* and *BTF size*. Table 2 depicts the results of linear fixed effects (logit) regressions. First of all, column (1) and (2)[36] show the logit results where the dependent variable is *BTF Dummy*, a dummy variable that equals 1 if the merger agreement includes a bidder termination fee provision, and 0 otherwise. Regressions (3)–(7) then show the results for the baseline regression, the continuous variable *BTF size*. Consistent with hypothesis 1, the coefficient on *Tgt Know Cap Stock* is positive and highly statistically significant at the 1% level across all specifications[37]. The relation is also economically significant as a one-standard deviation increase in this target R&D intensity measure is associated with a 0.57% increase in the size of the BTF. As I argue in Section 2, by building on prior research, organizational capital may be transferred through mergers, yet it does not represent a secret component that is highly valuable outside the firm. Of course, investment in key employees through training, advertising, and brand value is important as well and surely enables a organization to be more efficient,

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[36] These two regressions only differ in using different measures for acquiring firm's financial constraints. In the first regression, I include general M&A literature controls for the acquirer, such as its market capitalization, stock return volatility, market leverage and a dividend payer dummy to control for acquirer's financial strength that might affect the probability of providing a BTF. In the second regression, I remove these variables and include only the Hadlock and Pierce (2010) *SA-Index*.

[37] Figure A1 in the Appendix plots the relation between the pure values *BTF size (USD mm)* and *Tgt Knowledge Capital (USD mm)*, revealing a positive relation without controlling for other covariates affecting bidder termination fee size and target's knowledge capital stock. Despite the large number of control variables I'm not concerned with any multicollinearity problems given that variance inflation factors (vifs) are all below three and for the main variables of interest always below 1.6. In untabulated regressions, I additionally include more granular fixed effects and additionally cluster standard errors on the acquiring firm, finding that my results are qualitatively and quantitatively unchanged.

but it cannot be directly exploited by competitors[38]. Hence, the coefficient on *Tgt Org Cap Stock* is positive but statistically not different from zero, consistent with above mentioned argumentation and assumption.

Table 2

Target Firm's Intellectual Property Value and Bidder Termination Fees

Table 2 presents the results of fixed effects (FE) logit regressions ((1) and (2)) of *BTF Dummy*, a dummy variable that equals 1 if the merger agreement includes a bidder termination fee provision, and 0 otherwise, on the variable of interest, *Tgt Know Cap Stock*, a variable that captures the accumulated and depreciated R&D expenses of the target firm (in USD mm) over the last ten fiscal years prior to offer announcement, scaled by the market capitalization (also in USD mm) of the target firm 42 trading days prior to offer announcement (regressions (1) and (2)). I further include control variables as defined in Section 3. In regressions (3)–(7), the dependent variable is the continuous variable *BTF Size*, the (USD mm) amount of the bidder termination fee divided by the market capitalization (also in USD mm) of the target firm 42 trading days prior to offer announcement and expressed in percentage points. All regressions include *Acquirer Industry* × *Year Fixed Effects*, *Target Industry Fixed Effects* as well as an intercept but are unreported. All standard errors (in parentheses) are adjusted for heteroskedasticity (White (1980)) and within-cluster correlation. Models (1) and (2) include odds ratios [in angular parentheses], that relate to the change in the probability of including a bidder termination fee provision for a one-unit increase in a continuous variable, or a shift from zero to one for a dummy variable. (7) is a Tobit (censored at zero). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	BTF Dummy		BTF Size				
Regression Type	Logit FE		Linear FE				Tobit FE
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Target Firm Characteristics							
Tgt Know Cap Stock	0.954** (0.400) [3.528]	0.816** (0.382) [3.189]	1.051*** (0.267)	0.846*** (0.296)	1.004*** (0.276)	1.183*** (0.239)	3.062*** (0.589)
Tgt Org Cap Stock	0.043 (0.181) [1.247]	0.093 (0.187) [1.241]	0.178 (0.258)	0.045 (0.244)	0.136 (0.293)	0.139 (0.243)	0.731 (0.726)
Tgt Total Intangibles Ratio [OA–22]	0.115 (0.611) [1.250]	0.309 (0.599) [2.324]	1.703** (0.794)	1.858** (0.800)	1.688** (0.786)	1.312* (0.766)	4.278* (2.218)
Tgt Tangibility [OA–22]	−0.347 (0.656) [0.980]	−0.331 (0.675) [0.809]	0.248 (1.176)	0.275 (1.171)	0.505 (1.272)	0.843 (1.282)	0.668 (2.680)
Tgt Market-to-Book [OA–22]	0.020 (0.024) [1.042]	0.020 (0.024) [1.034]	0.009 (0.036)	0.015 (0.038)	0.010 (0.037)	0.026 (0.039)	0.084 (0.077)
Deal Characteristics							
Tgt Initiation	−0.518** (0.213) [0.564]	−0.511** (0.216) [0.587]	−0.793** (0.316)	−0.835** (0.321)	−0.696** (0.313)	−0.704** (0.316)	−2.919*** (0.906)

[38] Many intangibles that are driven by organizational (SG&A) capital stocks are by law inextricably bound to the firm and/or simply not exploitable, such as trademarks, brands and brand identity, copyrights, licenses, the firm's reliable vendor and distribution network, and internal technology systems and organizational processes, just to name a few.

Auction	−0.352* (0.197) [0.655]	−0.278 (0.201) [0.659]	−0.119 (0.276)	−0.136 (0.275)	−0.103 (0.280)	−0.274 (0.281)	−0.405 (0.806)
TTF Dummy	2.930*** (1.071) [18.248]	2.966*** (1.098) [22.078]					
TTF Size			0.026 (0.062)	0.015 (0.064)	0.029 (0.059)	0.007 (0.055)	−0.150 (0.251)
Deal Value	0.042 (0.030) [1.057]	0.018 (0.017) [1.036]	0.012 (0.031)	0.017 (0.031)	0.012 (0.024)	0.009 (0.023)	0.069 (0.068)
Friendly	0.062 (0.899) [1.175]	0.274 (0.912) [1.286]	−0.634 (1.277)	−0.668 (1.261)	−0.136 (1.264)	−0.429 (1.225)	−0.489 (3.032)
Cash Only	−0.924*** (0.280) [0.332]	−0.967*** (0.304) [0.312]	−0.668* (0.349)	−0.726** (0.346)	−0.618 (0.380)	−1.062*** (0.286)	−3.116*** (1.081)
Tender Offer	−1.347*** (0.460) [0.181]	−1.363*** (0.458) [0.178]	−1.355*** (0.405)	−1.394*** (0.402)	−1.418*** (0.386)	−1.201*** (0.420)	−6.758*** (1.763)
Horizontal Takeover	0.051 (0.203) [1.117]	0.144 (0.207) [1.205]	0.128 (0.255)	0.131 (0.256)	0.128 (0.250)	0.136 (0.247)	0.858 (0.722)
Relative Size Market Cap [OA–22]	−0.027 (0.034) [0.985]	−0.030 (0.034) [0.982]	−0.001 (0.001)	−0.001 (0.001)	−0.001* (0.001)	−0.002*** (0.000)	−0.018 (0.019)
Post Closing Highly Conc Industry	0.665* (0.357) [2.675]	0.588 (0.358) [2.337]	2.188** (0.880)	2.198** (0.876)	1.909** (0.831)	1.196* (0.636)	4.276*** (1.578)
Acq All Financial Advisor Fees Deal Value	−0.007 (0.185) [0.980]	0.032 (0.187) [1.039]	−0.126 (0.215)		−0.169 (0.256)	0.032 (0.258)	−0.768 (0.775)
Tgt All Financial Advisor Fees Deal Value	−0.409*** (0.157) [0.620]	−0.371** (0.166) [0.654]	−0.224 (0.149)		−0.213 (0.144)	−0.325** (0.140)	−0.874 (0.624)
Acquiring Firm Characteristics							
Acq Market Cap [OA–22]	−0.008 (0.009) [0.992]		0.001 (0.008)	0.002 (0.008)			−0.013 (0.024)
ln Acq 1YR Stock Return Volatility [OA–1]	0.305 (0.260) [1.521]		0.620 (0.426)	0.586 (0.425)			1.455 (1.211)
Acq Market Leverage [OA–22]	1.084 (0.773) [1.863]		1.452 (1.099)	1.139 (1.094)			2.866 (2.991)
Acq Dividend Payer	−0.379 (0.233) [0.732]		−0.874** (0.427)	−0.843* (0.433)			−2.014** (1.014)
Acq Market-to-Book [OA–22]	−0.032 (0.024) [0.961]	−0.028 (0.022) [0.961]	−0.040* (0.021)	−0.041* (0.021)	−0.046** (0.020)	−0.035 (0.024)	−0.137* (0.076)
Acq Hadlock-Pierce-Index		0.403 (0.280) [1.758]			0.898** (0.430)		
Acq Whited-Wu-Index						−0.089 (0.101)	

Acq Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tgt Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	769	751	769	769	751	697	769
Pseudo R^2	0.302	0.298					0.138
Adjusted R^2			0.103	0.100	0.096	0.111	

(Table 2 continued)

The firm's total intangibles that are capitalized on the balance sheet also comprise patents and patent licenses. This intellectual property is protected by law from copying, making, and selling by other parties, and may have been externally acquired through target's prior acquisitions and further developed by the firm. Through its direct proximity to intellectual property, I thus expect *Tgt Total Intangibles Ratio* also to be related to *BTF size*, which is indeed the case, albeit somewhat weaker correlated at the 5% and 10% level (specification (6)). *Tgt Initiation* is negatively and statistically significantly related to *BTF size* in all specifications, consistent with the notion that target's intentions to sell itself and proactively initiate the deal plays a central role (Masulis and Simsir (2018)): in these cases, a significant amount of bargaining power is shifted to the acquirer, which systematically lowers the willingness for the latter to provide a BTF, all else equal. (Pure) cash deals are usually smaller, thus, controlling for relative size between the firms, represent less risky deals in terms of obtaining regulatory approval, acquirer's uncertainty over its ability to pay for the deal and acquirer's shareholder approval. Consistent with this reasoning, the coefficient on the dummy variable *Cash Only* is negative and statistically significantly related to *BTF size*. This is also true for tender offers, since these type of acquisitions sometimes circumvent target firm's management, thereby also bypass deal negotiations and hence reduce the likelihood to provide a BTF.

Since *BTF size* is left-censored (truncated) at zero, I also estimate a fixed effects tobit model (specification (7)). The marginal effect on *Tgt Know Cap Stock* becomes even larger (3.062 vs. 1.051). Additionally, Table A3 in the Appendix provides a modular regression setup, which highlights that the hypothesized positive relation is not a random outcome of an appropriately chosen regression model, but rather an association that is valid and economically meaningful, independent of selected covariates and fixed effects.

Taken together, if looking at off-balance sheet intangibles in M&A, the results suggest that only the "secrecy" component, represented through *Tgt Know Cap Stock* – and not its organizational capital value – is a reliable and significant driver of BTF inclusion in M&A contracts as well as *BTF size*. This suggests that R&D-intense targets can utilize their bargaining power in deal negotiations to convince the prospective acquirer to provide an appropriately priced bidder termination fee. Consequently, hypothesis 1 is strongly supported.

4.3 Identification: Instrumental Variables Approach

A common concern in the empirical finance literature is, that despite controlling for many factors explaining the cross-sectional distribution of the dependent variable, there might be endogeneity concerns. In my case, this might be particularly true if there would exist a reverse causality of *BTF size* affecting target firm's R&D investments[39], omitted variables, and/or error-in-variables, i.e., if I measure my variable of interest with error. To address these concerns and to strenghten the causal interpretation of this paper, I apply a two-stage least squares (2SLS)[40] instrumental variables estimation. For my instrument to be valid, it has to fulfill two vital conditions: first, the instrument must be relevant, i.e., it must be correlated with the (possibly) endogenous variable *Tgt Know Cap Stock* in the first stage of the regression equation[41], conditionally on the other covariates, and second, the instrument must be exogenous, i.e., the instrument must not be correlated with the error term in the second stage, the structural equation, also conditionally on the other covariates.

I suggest two instruments, but focus on one specifically: *Tgt SIC2 Industry R&D Worker Ratio*. This variable is defined as the ratio of knowledge workers in strictly R&D-related jobs to the total number of surveyed participants in a given SIC2 industry-year. R&D-related jobs are defined as all jobs (occupations, denoted "occsoc" in the survey data) coded between 1510XX and 1940YY in the annual American Community Survey (ACS) of the U.S. Census Bureau. These survey data are included in the Integrated Public Use Microdata Series

[39] Concerning reverse causality, it seems highly unlikely that the size of the negotiated BTF in a M&A deal affects firm-level R&D activity (if empirically existent at all, the effect running from *BTF size* to *Tgt Know Cap Stock* should be negligibly small).

[40] I receive similar results applying LIML or GMM instead of 2SLS.

[41] I.e., it must be a reliable predictor for *Tgt Know Cap Stock*, with a statistically significant non-zero coefficient in the reduced form (first stage) equation. I include *Target Industry Fixed Effects*, since they are based on the first of all four SIC digits, thus sufficient variation remains (instrument is SIC2 level).

(IPUMS USA (2020)). Since IPUMS does not directly provide industry definitions in the SIC code format, I manually assign each census code industry definition to the most suitable SIC2 industry[42] and cross-check each industry assignment with the NAICS definition codes, which are available for both datasets. The R&D worker ratios are mapped on a SIC2 industry-year basis to each target firm in the sample on the last fiscal year end date prior to offer announcement. The economic intuition behind this instrument variable is that *Tgt SIC2 Industry R&D Worker Ratio* represents labor supply in target firm's industry: higher values create an incentive for the firm to invest in R&D given its availability of skilled workers that can create valuable innovation and enables the firm to stay competitive. Therefore, I claim that this ratio is by itself likely directly uncorrelated with deal-level *BTF size*, and only correlated with the dependent variable through its correlation with *Tgt Know Cap Stock*. Although there doesn't seem to exist a theoretical link between the instrument and *BTF size*[43] and given one cannot control for instrument exogeneity directly, I include a second instrument to at least be able to test against the null hypothesis that over-identifying restrictions are valid. The second instrument is *Tgt Trade Secrecy Mention Count in 10-K*, the number of mentions of either "trade secret", "trade secrets" and/or "trade secrecy" in target firm's most recent 10-K report filed with the SEC prior to offer announcement. I expect this variable also to be correlated with *Tgt Know Cap Stock*, since R&D-intense firms are likely to have trade secrets and name it more often, the more relevance it has for their firm. Table 3 shows the 2SLS IV regression results.

As expected, *Tgt SIC2 Industry R&D Worker Ratio* is positively and statistically highly significantly related to *Tgt Know Cap Stock**, the predicted value for targets knowledge capital stock (column (1)). Moreover, the first stage is also strong with an effective F-statistic of 13.701 (applying the STATA™ routine developed in Montiel Olea and Pflueger (2013)), exceeding the rule-of-thumb value of ten. This suggests that the instrument has sufficient explanatory power for *Tgt Know Cap Stock*, thus meeting the relevance condition. In the second stage

[42] Granular SIC2-level data with detailed mapping are available upon request.

[43] Additionally, in untabulated regressions I include both instruments in the baseline regression and find no significant relation between these instruments and *BTF size*, while the strong positive relation between *Tgt Know Cap Stock* and *BTF size* remains. A pairwise correlation test among these variables and *BTF size* reveals only a weak and insignificant correlation, not controlling for other factors. The number of observations drops slightly due to the availability of respective instrumental variables.

Table 3

Instrumental Variables Estimation – Target Firm's SIC2 Industry R&D Worker Ratio

This table reports the results of linear fixed effects two-stage least squares (2SLS) instrumental variables regressions of *BTF Size* on *Tgt Know Cap Stock*. In models (1) and (2), the first stage (*Tgt Know Cap Stock**) is estimated using the target firm's SIC2 industry R&D worker ratio, *Tgt SIC2 Industry R&D Worker Ratio*, as the instrument. In models (3) and (4), I further include the number that counts how often the word group "trade secret", "trade secrets" and/or "trade secrecy" is mentioned in target firm's most recent 10-K report filed with the SEC prior to offer announcement, *Tgt Trade Secrecy Mention Count in 10-K*, as an instrument. All regressions include *Acquirer Industry × Year Fixed Effects* and *Target Industry Fixed Effects* but are unreported. All standard errors (in parentheses) are adjusted for heteroskedasticity (White (1980)) and automatically adjusted in the 2[nd] stage (applying the STATA™ *xtivreg2* 2SLS command developed in Schaffer (2010)). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	BTF Size			
	1[st] Stage	2[nd] Stage	1[st] Stage	2[nd] Stage
Independent Variables	(1)	(2)	(3)	(4)
Target Firm Characteristics				
Tgt Know Cap Stock*		5.073**		3.670**
		(2.141)		(1.643)
Tgt SIC2 Industry R&D Worker Ratio	1.419***		1.297***	
	(0.383)		(0.393)	
Tgt Trade Secrecy Mention Count in 10-K			0.020**	
			(0.009)	
Tgt Org Cap Stock	0.059*	−0.037	0.067*	0.102
	(0.035)	(0.312)	(0.036)	(0.282)
Tgt Total Intangibles Ratio [OA–22]	−0.059	1.775*	−0.071	1.744**
	(0.114)	(0.918)	(0.114)	(0.870)
Intercept	−1.315***	5.221	−1.259***	4.041
	(0.454)	(4.069)	(0.455)	(3.631)
Other Target Firm Characteristics	Yes	Yes	Yes	Yes
Deal Characteristics	Yes	Yes	Yes	Yes
Acquiring Firm Characteristics	Yes	Yes	Yes	Yes
Acq Industry × Year FE	Yes	Yes	Yes	Yes
Tgt Industry FE	Yes	Yes	Yes	Yes
Observations	753	753	735	735
Adjusted R^2	0.407	0.102	0.423	0.032
1[st] Stage F^{eff}-statistic (MOP)	13.701		10.329	
{p-value}	{0.000}		{0.000}	
[Stock-Yogo weak ID F-test 15% critical value]	[8.960]		[11.590]	
χ^2-statistic (Sanderson-Windmeijer (2016))	16.830		25.560	
{p-value}	{0.000}		{0.000}	
J-statistic (Sargan-Hansen) {p-value}				0.780
				{0.377}
Model p-value	0.000	0.000	0.000	0.000

(column (2)), the coefficient on the predicted value, *Tgt Know Cap Stock**, is positive and statistically significant at the 5% level, and even larger than the marginal effect obtained in the baseline regression in column (3) in Table 2[44]. This finding is consistent with the study of Pancost and Schaller (2019), who find that the 2SLS coefficient is in fact larger than the OLS coefficient in 86% of their surveyed cases, even if theory suggests that the OLS coefficient should be inflated relative to the 2SLS coefficient. Their study also shows that the 2SLS approach resolves a substantial amount of attenuation bias resulting from classical errors-in-variables. My inference remains unchanged if I replace the instrument with its lagged values.

I receive qualitatively and quantitatively similar results in the regression setup with both instruments as presented in columns (3) and (4). Both IVs are strongly correlated with the predicted value in the first stage, although exhibit a somewhat weaker effective F-statistic of 10.329. Also, the Sargan-Hansen (Sargan (1958)) over-identification test (see, e.g., Hayashi (2000)) is unable to reject the null hypothesis that the instruments satisfy the exclusion restriction (J-statistic is 0.780 with a p-value of 0.377). Since the Stock and Yogo (2005) weak identification F-test 15% critical value is slightly larger with a value of 11.590 and thus slightly "worse" – though also reliable – compared to the single IV approach, I focus on the results of columns (1) and (2) for causal interpretation. Thus, after exploiting this exogenous source of economically meaningful and directly related R&D-intensity variation, I conclude that my findings are robust to this method of endogeneity correction. The baseline effect likely underestimates the true relation between target's intellectual property value and the size of the negotiated bidder termination fee.

4.4 Baseline Regression Results: Short-Term Target Firm Value Effects around Deal Resolution

To logically complete my story of the BTF compensating the target for revealing private information and important business and technology secrets during negotiations, I also need to consider what is happening if acquirers really terminate deals. Although the prospective deal, once officially announced, receives public attention and market participants price in and

[44] Second stage's standard errors are adjusted accordingly, applying STATA™'s *xtivreg2* command.

regularly update their beliefs about the probability of deal completion, acquirer-induced deal failure may be a surprise for target shareholders. This makes an event study approach feasible, since it is then exogenous to target's stock price movement. As put forward in Section 2, I expect it to be beneficial for the target if the acquirer abandons the deal and pays a bidder termination fee, in contrast to the benchmark case in which the deal is terminated and no BTF is paid. Following hypothesis 2, this relation should increase in the size of the BTF (i.e., the received payment scaled by target's size). Table 4 presents the results of an event study at deal resolution.

Acq Induced Cancellation is a dummy variable that equals 1 if the acquirer induced the cancellation of the deal, and 0 otherwise. Specification (1) regresses target's cumulative abnormal deal resolution returns on *BTF Dummy* and *Acq Induced Cancellation* alone, which does not indicate a significant relation. In regression (2), however, the coefficient on the included interaction term *Acq Induced Cancellation* × *BTF Dummy* is positive and statistically highly significant at the 1% level.

The results hold if I repeat these two regressions with the continuous variable *BTF Size* instead of its dummy variable (regressions (3) and (4)). Consistent with hypothesis 2, the coefficient on *Acq Induced Cancellation* × *BTF Size* is positive and statistically significant at the 5% level. This supports the view that deal termination by the acquirer and the associated payment of the bidder termination fee is beneficial for the target, and that this relation increases in the size of the BTF, as compared to the case if the deal is terminated and no BTF is agreed on in the merger contract.

By including the dummy variable *Third Party Competing Bid Cancellation*, I additionally control for deal termination by third parties. This usually happens if a topping bid from another bidder emerges. Since target boards have to consider any bid until successful (target) shareholder approval, competing bids, if they arise, are often higher. The positive and statistically significant coefficient across all specifications is in line with this reasoning. The same holds for *Deal Completion*, where I find the relation to target's cumulative abnormal deal reaolution returns also to be positive. I include acquirer and target characteristics according to the target cumulative abnormal deal resolution return regressions in Malmendier et al. (2016).

Table 4

Short-Term Target Firm Value Effects around Deal Resolution

Table 4 presents the results of linear fixed effects regressions of target firm's cumulative abnormal deal resolution returns on two variables of interest, first, the interaction term *Acq Induced Cancellation* × *BTF Dummy* (regression (2)), and second, the interaction term *Acq Induced Cancellation* × *BTF Size* (regression (4)). *Acq Induced Cancellation* is a dummy variable that equals 1 if the acquirer induced the cancellation of the deal, and 0 otherwise, *BTF Dummy* is a dummy variable that equals 1 if the merger agreement includes a bidder termination fee provision, and 0 otherwise, and *BTF Size* is USD (mm) amount of the bidder termination fee divided by the market capitalization (also in USD mm) of the target firm 42 trading days prior to offer announcement and expressed in percentage points. *C4 CAR* denote Carhart's (1997) four-factor model to model normal returns (cumulative abnormal returns). *Third Party Competing Bid Cancellation* is a dummy variable that equals 1 if the deal was cancelled due to a third party bid for the target that led to the cancellation of the original bid, and 0 otherwise. *Deal Completion* is a dummy variable that equals 1 if the deal was closed successfully, and 0 if cancelled. *Acq Hadlock-Pierce-Index* is a measure for acquiring firm's financial constraints, proposed by Hadlock and Pierce (2010). I further include *Deal Characteristics* as well as market-to-book ratios and stock return volatility measures for both the target and the acquirer (as outlined in Section 3). All regressions include *Target Industry* × *Deal Resolution Year Fixed Effects* as well as an intercept but are unreported. All standard errors (in parentheses) are adjusted for heteroskedasticity (White (1980)) and within-cluster correlation. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Tgt C4 CAR			
Event Window	[−3;+3]			
Independent Variables	(1)	(2)	(3)	(4)
BTF Dummy	1.405	1.193		
	(0.859)	(0.870)		
Acq Induced Cancellation × BTF Dummy		15.632***		
		(5.517)		
Acq Induced Cancellation	1.729	−9.284	1.789	−5.485
	(4.845)	(5.907)	(4.902)	(5.907)
Acq Induced Cancellation × BTF Size				1.832**
				(0.922)
BTF Size			0.125	0.100
			(0.116)	(0.114)
Third Party Competing Bid Cancellation	9.454**	9.397**	9.482**	9.583**
	(4.685)	(4.638)	(4.647)	(4.582)
Deal Completion	10.210***	10.115***	10.255***	10.211***
	(3.478)	(3.498)	(3.527)	(3.536)
Acq Hadlock-Pierce-Index	0.104	0.287	0.056	0.191
	(0.572)	(0.576)	(0.611)	(0.617)
Other Deal Characteristics	Yes	Yes	Yes	Yes
Acq & Tgt: MTB & Stock Return Volatility	Yes	Yes	Yes	Yes
Tgt Industry × Deal Resolution Year FE	Yes	Yes	Yes	Yes
Observations	497	497	497	497
Adjusted R^2	0.113	0.139	0.109	0.126

4.5 Interaction between Intellectual Property Protection and Firm Pair Characteristics

Technological Proximity between Acquirer and Target

Building on the theoretical reasoning developed for hypothesis 3a, the relation between target firm's knowledge capital stock value and BTF size should increase in the degree of technological proximity between the acquirer and the target. The more close the merger pair's knowledge base is, the more likely they are competing not only in product market space, but they also more likely compete among applying and developing technological advances to enhance innovation. I furthermore claim that the knowledge capital of the target firm can be better ascertained by an acquirer that innovates in a similar technology space.

To quantify the degree of technological proximity between merging firms, I propose the spillover-adjusted Mahalanobis extension of the Jaffe (1986) technological similarity measure, developed in Bloom, Schankerman, and Van Reenen (2013), which has certain advantages over the generic measure. Jaffe's (1986) measure, in the context of merging firms, is defined as the following positive correlation coefficient, bound between 0 and 1[45]:

$$Tech\ Prox_{Acq,Tgt} = \frac{T_{Acq} T_{Tgt}^{'}}{\sqrt{T_{Acq} T_{Acq}^{'}} \sqrt{T_{Tgt} T_{Tgt}^{'}}}$$

Most important, the Bloom et al. (2013) measure allows for spillovers between different technology classes[46], which are defined by the United States Patent and Trademark Office (USPTO) to classify patents. To measure spillovers, they argue that if two technologies are often located together in the same firm (e.g., "computer input/output" and "computer processing"), spillovers will be greater, because the distance between the technologies is smaller. They proxy for this Mahalanobis distance by the share of times the two technology classes are

[45] First, all of the firm's patents between 1970 and 2006 are allocated into the different 426 USPTO technology classes, defining the scope-of-innovation-activity-vector $T_i = (T_{i1}, T_{i2}, T_{i3}, ..., T_{i426})$ for firm i where $T_{i\tau}$ is the share of firm i's patents in technology class τ, i.e., $T_{i\tau}$ is the ratio of the number of awarded patents to firm i in technology class τ to the total number of awarded patents in all technology classes over the whole period since 1970. The results are robust to using the unadjusted measure instead.
[46] This is ruled out by the Jaffe (1986) measure, which assumes technological spillovers only within the same class and no spillovers to and from other classes.

patented within the same firm[47]. In order to make an economically meaningful statement, I calculate their adjusted measure for all acquirer-target firm pairs in my sample by using their algorithm[48], split the sample at the median value for Technological Proximity (*Tech Prox*), generate a dummy that equals 1 if *Tech Prox* is above the sample median, 0 otherwise, and interact this dummy (*Tech Prox Median*) with my variable of interest, *Tgt Know Cap Stock*. Table 5 presents the regression results.

Table 5

Interaction between Intellectual Property Protection and Technological Proximity

This table shows the results of linear fixed effects regressions of *BTF Size* on the variable of interest, the interaction term *Tgt Know Cap Stock* × *Tech Prox Median*. *Tech Prox Median* is a dummy variable that equals 1 if the values for *Technological Proximity* are above the sample median, and 0 otherwise. *Technological Proximity* is defined as the spillover-adjusted correlation coefficient of patenting across United States Patent and Trademark Office (USPTO) technology classes between pairs of firms (i.e., acquirer-target pairs in the sample, see Table A1 (Panel B) in the Appendix for a detailed definition). Regression (2) is the same as regression (1), except that I include *Tech Prox Missing (zero)*, a dummy variable that equals 1 if the acquirer-target pair's value for *Technological Proximity* is zero or if either the acquirer and/or the target firm hasn't been granted a patent from the USPTO since 1970. Data on *Technological Proximity* are obtained from Nicholas Bloom's website (see Lucking, Bloom, and Van Reenen (2018), and Bloom et al. (2013)). As a robustness test, I restrict the sample in regression (3) to observations in which the value for *Technological Proximity* is strictly larger than zero (in Table A4 in the Appendix I additionally fit a Heckman (1979) selection model). All regressions include *Acquirer Industry* × *Year Fixed Effects*, *Target Industry Fixed Effects* as well as an intercept but are unreported. All standard errors (in parentheses) are adjusted for heteroskedasticity (White (1980)) and within-cluster correlation. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	BTF Size		
	Full Sample		Tech Prox > 0
Independent Variables	(1)	(2)	(3)
Tech Prox Missing (zero)		0.029	
		(0.625)	
Tech Prox Median	−0.650	−0.635	0.242
	(0.569)	(0.587)	(0.351)
Tgt Know Cap Stock × Tech Prox Median	1.545***	1.544***	0.955*
	(0.444)	(0.441)	(0.548)
Tgt Know Cap Stock	0.855***	0.856***	0.715*
	(0.304)	(0.308)	(0.388)

[47] The result is an adjusted technology closeness measure that weights the overlap in patent shares between firms by how close their different patent shares are to each other. "The same patent class in different firms is given a weight of 1, and different patent classes in different firms are given a weight between 0 and 1, depending on how frequently they overlap within firms [...].", see the detailed description in their updated paper (Lucking, Bloom, and Van Reenen (2018)).

[48] Provided on Nicholas Bloom's website: https://nbloom.people.stanford.edu/research.

	(1)	(2)	(3)
Tgt Org Cap Stock	0.046 (0.261)	0.046 (0.261)	−0.378 (0.612)
Controls	Yes	Yes	Yes
Acq Industry × Year FE	Yes	Yes	Yes
Tgt Industry FE	Yes	Yes	Yes
Observations	769	769	233
Adjusted R^2	0.108	0.107	0.384

(Table 5 continued)

As suggested by hypothesis 3a, the coefficients on *Tgt Know Cap Stock* and the interaction term, *Tgt Know Cap Stock* × *Tech Prox Median*, are both positive and statistically highly significant at the 1% level (specification (1)). The results are qualitatively and quantitatively unchanged if I additionally control for acquirer-target firm pairs having a *Tech Prox* correlation coefficient of zero (column (2)), which is the case if one or both firms haven't been granted a patent since 1970. Regression specification (3) shows the results for *Tech Prox* values strictly larger than zero, i.e., only for patenting firms, where I find the inference to also remain unchanged[49]. These results strongly support hypothesis 3a.

Product Market Rivalry between Acquirer and Target

Hypothesis 3b posits that, all else equal, the baseline relation should increase in the degree of competition between the merging firms. The reason is that a directly competing acquirer could gain the most from exploiting target's private information and innovation by successfully capitalizing them and increasing his market share by simultaneously weakening the target as a competitor. On the other hand, if the merging firm pair has no common relation in product market space, incentives to exploit information should be smaller.

Quantifying a comparable degree of product market rivalry at the detailed firm-firm-level is difficult. Well-known industry classifications such as the SIC or NAICS definitions fail to provide firm-firm-specific measures, are somewhat rigid since they are slow to update over time, and are based on production processes and not necessarily the products and services

[49] Although at a somewhat weaker statistical significance level, since the number of observations drop from 769 to 233. Table A4 in the Appendix provides additional support for the results after controlling for sample selection with respect to successfully patenting firm pairs, applying a Heckman (1979) correction model.

finally offered by the firm (Frésard et al. (2020)). To overcome these pitfalls of old classifications, I apply the textual product market similarity score based on firms' 10-K filings, developed by Hoberg and Phillips (2010, 2016), to measure the degree of firm-firm-year-specific competition. Their Text-based Network Industry Classifications (TNIC) are generated by parsing the product descriptions from the firms' 10-Ks and forming word vectors for each firm to compute continuous measures of product similarity for every pair of firms in the CRSP/Compustat universe in each year (a pairwise similarity matrix). This correlation coefficient has the advantage of quickly reacting to changes in product descriptions[50]. The higher their score, the closer the two firms are product market rivals. I match their firm-firm-year-level pairwise similarity score with the merging acquirer-target firm pairs in the sample and define tercile dummies based on their values which are then interacted with *Tgt Know Cap Stock*. TNIC1, TNIC2, and TNIC3 represent calibrations similar to different industry definition granularities: TNIC1 is the complete version and most detailed of the standard TNIC network developed by Hoberg and Phillips (2010, 2016) with all firm pairs included (even those that are very weakly related). TNIC2 matches the granularity of SIC2-level industries, and TNIC3 the granularity of SIC3-level industries. Table 6 depicts the results of regressions including these similarity measures.

As claimed by hypothesis 3b, the coefficient on the interaction term *Tgt Know Cap Stock* × *Top Tercile PMS $_{TNIC1}$* is positive and highly statistically significant at the 1% level for the baseline *BTF size* regression (specifications (4)–(6), depending on the granularity of industry definitions). Columns (1)–(3) show the results for the fixed effects logit regressions of *BTF Dummy*, an indicator variable that equals 1 if a BTF is negotiated between the merging parties, and 0 otherwise, where the coefficient is also significant at the 5% level. The results from both regression types suggest that the relation between target firm's knowledge capital stock value and the size of the bidder termination fee is increasing in the firm pair's degree of product market rivalry, independent of the ex-ante determined industry granularities, and thus

[50] Hoberg and Phillips state on their data website: "These product descriptions are legally required to be accurate, as Item 101 of Regulation S-K legally requires that firms describe the significant products they offer to the market, and these descriptions must also be updated and representative of the current fiscal year of the 10-K." This is to make sure that the descriptions are reliable. Misuse can be enforced by the SEC, hence firms have a strong ex-ante incentive to report truthfully.

strongly support hypothesis 3b. Taken together, the results indicate that new innovation – generated through R&D – can be most valuable for firms with a similar technology base and firms that are direct competitors.

Table 6

Interaction between Intellectual Property Protection and Product Market Rivalry

Table 6 presents the results of linear fixed effects regressions of *BTF Size* on a set of variables of interest, the interaction terms between *Tgt Know Cap Stock* and different quantiles of *Product Market Similarity (PMS)*. *Top Tercile PMS* is a dummy variable that equals 1 if the value of *Product Market Similarity (PMS)* is in the top (highest) tercile of its distribution, and 0 otherwise. *Product Market Similarity (PMS)* is a yearly firm-by-firm pairwise product market similarity score (real number in the interval [0,1]) calculated for each firm-firm-fiscal-year combination by parsing the product descriptions from the firms' annual 10-Ks and forming word vectors for each firm to compute continuous measures of product similarity for every pair of firms in the sample in each year (a pairwise similarity matrix). A higher score relates to a higher word similarity (i.e., the text of the two firms' business descriptions has more common vocabulary than a pair of firms with a lower score), used as a proxy for product similarity and thus product-market rivalry, i.e., firm pairs with a higher score are "nearer" rivals. The index (TNIC1, TNIC2, and TNIC3) refer to the granularity between the two firms with TNIC1 being of highest (most detailed) granularity which explains the decrease in observations from regression (1) to regression (3), and (4) to (6), respectively (see Table A1 (Panel B) in the Appendix for a detailed definition). All Text-based Network Industry Classifications (TNIC) data are obtained from the Hoberg-Phillips Data Library (Hoberg and Phillips (2010, 2016)). All regressions include *Acquirer Industry × Year Fixed Effects*, *Target Industry Fixed Effects* as well as an intercept but are unreported. All standard errors (in parentheses) are adjusted for heteroskedasticity (White (1980)) and within-cluster correlation. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	BTF Dummy			BTF Size		
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Top Tercile PMS $_{TNIC1}$	−0.205			−0.194		
	(0.311)			(0.398)		
Med Tercile PMS $_{TNIC1}$	−0.080			−0.120		
	(0.301)			(0.376)		
Tgt Know Cap Stock × Top Tercile PMS $_{TNIC1}$	2.985**			2.220***		
	(1.485)			(0.561)		
Tgt Know Cap Stock × Med Tercile PMS $_{TNIC1}$	−0.823			−0.274		
	(1.224)			(0.516)		
Top Tercile PMS $_{TNIC2}$		−0.585			−0.750*	
		(0.360)			(0.423)	
Med Tercile PMS $_{TNIC2}$		−0.378			−0.571	
		(0.372)			(0.380)	
Tgt Know Cap Stock × Top Tercile PMS $_{TNIC2}$		3.055**			2.359***	
		(1.466)			(0.623)	
Tgt Know Cap Stock × Med Tercile PMS $_{TNIC2}$		1.176			0.008	
		(1.566)			(0.569)	
Top Tercile PMS $_{TNIC3}$			−0.345			−0.490
			(0.367)			(0.466)
Med Tercile PMS $_{TNIC3}$			−0.535			−0.521
			(0.409)			(0.491)
Tgt Know Cap Stock × Top Tercile PMS $_{TNIC3}$			3.511*			1.772*
			(1.851)			(1.038)

Tgt Know Cap Stock × Med Tercile PMS $_{TNIC3}$			3.463			−0.078
			(2.209)			(0.957)
Tgt Know Cap Stock	−0.010	−0.595	−1.230	0.271	0.092	0.525
	(1.127)	(1.089)	(1.684)	(0.505)	(0.613)	(0.924)
Tgt Org Cap Stock	0.070	0.115	0.142	−0.141	−0.040	0.080
	(0.204)	(0.211)	(0.232)	(0.208)	(0.239)	(0.312)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Acq Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Tgt Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	694	603	525	694	603	525
Pseudo R^2	0.339	0.422	0.415			
Adjusted R^2				0.115	0.195	0.203

(Table 6 continued)

5 Robustness Tests

The following results aim to underpin the story developed in this paper by first discussing subsample regressions where I find the effect between target's intellectual property value and BTF size to be more pronounced. Second, I provide evidence that my regression results are robust to different scaling, i.e., by relating the dollar values of both BTF and target's knowledge capital stock to different reference values, emphasizing the economic magnitude of the relation. Third, I show that target firm's knowledge capital stock is a reliable and highly significant determinant of both its patenting activity as well as the likelihood to mention trade secrets in its 10-K report. Including these innovation outcome variables directly in the main regression would raise a bad control concern (Angrist and Pischke (2008)). Lastly, I show that my results are robust to including proxies controlling for the degree of information diffusion from the target to the acquirer.

5.1 Subsample Tests

Table 7 presents a set of subsample regressions that highlight where the effect is stronger or weaker, if not existent at all. First, in regressions (1) and (2), the sample is split by the median value of *Tgt 5YR Avrg Yearly Know Cap Growth*. This growth rate is defined as the average annualized growth rate of *Tgt Know Cap Stock* within the target firm calculated over the last five fiscal years prior to offer announcement. I hypothesize that the effect between

Tgt Know Cap Stock and *BTF size* should be more pronounced, if the target belongs to the pioneers in its technology sector, as proxied by above average investment increases in R&D. At the beginning of a technology wave, innovation is likely not yet protected by patents, and firms should have the highest incentive to increase their R&D investments, since there might only exist – if at all – a limited number of competitors. In turn, the target's private intellectual property then has the highest value for the acquirer in securing significant market shares. As hypothesized, the coefficient is positive and highly statistically significant only in the high growth rate regression (rate above sample median, (1)), and also positive, yet insignificant, in specification (2). This suggests that the relation remains positive during the saturation phase of the innovation wave, though less strong, since the marginal value of innovation effort to add new technology features typically decreases over time, consistent with Frésard et al. (2020).

Next, I expect the effect to be more pronounced for targets that rely very heavily on R&D in general. To gauge this dependency, I define *Tgt Know Cap Intensity* as the percentage share of *Tgt Know Cap Stock* on both intangible capital stocks (knowledge and organizational capital). Regression (3) and (4) depict the results, showing that the effect is positive and highly significant only for firms in the top quartile of the distribution of *Tgt Know Cap Intensity* (3).

Tgt Unique Product Industry is a dummy variable that equals 1 (Yes) if the target firm's industry is in the top quartile of all Fama-French 49 industries annually sorted by industry-median product uniqueness, 0 (No) otherwise, where product uniqueness is defined as all selling expenses scaled by sales[51]. According to Titman and Wessels (1988), firms that sell products with close substitutes are hypothesized to do less R&D since their innovations can be more easily duplicated. In addition, successful R&D projects are hypothesized to lead to new products that differ from those existing in the market. Consistent with this reasoning, the coefficient on *Tgt Know Cap Stock* is positive and statistically highly significant only in regression (5), i.e., for targets assigned to industries selling unique products.

Furthermore, if targets operate in industries where innovation may be one of the most important driving force, the main association claimed in this paper should also be strongest. I define *Tgt FF5 HTHC Industry* as a dummy variable that equals 1 if the target is assigned to

[51] Calculated following Titman and Wessels (1988) and Masulis, Wang, and Xie (2007).

Table 7

Robustness – Subsample Tests

The following table depicts the results of linear fixed effects regressions of *BTF Size* on *Tgt Know Cap Stock* and all control variables used in the baseline regression in Table 2, column (3), except that the full sample is split by various measures. In regressions (1) and (2), the sample is split by the median value of *Tgt 5YR Avrg Yearly Know Cap Growth*, which is the average annualized growth rate of *Tgt Know Cap Stock* within the target firm calculated over the last five fiscal years prior to offer announcement (given that I require the target firm to have at least full five years of valid R&D data prior to offer announcement, the sample is restricted to 324 observations). Regressions (3) and (4) are split by *Tgt Know Cap Intensity*, which is defined as *Tgt Know Cap Stock* divided by the sum of *Tgt Know Cap Stock* and *Tgt Org Cap Stock*. Regression (3) shows the results for the top quartile, regression (4) shows the results for the other remaining observations. *Tgt Unique Product Industry* (regressions (5) and (6)) is a dummy that equals 1 (Yes) if the target firm's industry is in the top quartile of all Fama-French 49 industries annually sorted by industry-median product uniqueness, 0 (No) otherwise, where product uniqueness is defined as all selling expenses scaled by sales. Regressions (7) and (8) are divided by *Tgt FF5 HTHC Industry*, a dummy variable that equals 1 if the target is assigned to the Fama-French 5 industry classification in either hightech (HT) or healthcare (HC), and 0 otherwise. In regressions (9) and (10), the sample is split by *Tgt Trade Secrecy Mention Count in 10-K*, which is the number of mentions of either "trade secret", "trade secrets" and/or "trade secrecy" in target firm's most recent 10-K report filed with the SEC prior to offer announcement. The reason I chose to split the sample by values strictly larger than (smaller or equal to) 1 is that in some cases the above mentioned words appear only in (standard) headlines in 10-K filings with no further explanantion if trade secrets really exist. All regressions include *Acquirer Industry* × *Year Fixed Effects*, *Target Industry Fixed Effects* as well as an intercept but are unreported. All standard errors (in parentheses) are adjusted for heteroskedasticity (White (1980)) and within-cluster correlation. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	BTF Size									
	Tgt 5YR Avrg Yearly Know Cap Growth		Tgt Know Cap Intensity		Tgt Unique Product Industry		Tgt FF5 HTHC Industry		Tgt Trade Secrecy Mention Count in 10-K	
	High	Low	High	Low	Yes	No	Yes	No	> 1	≤ 1
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Target Firm Characteristics										
Tgt Know Cap Stock	1.040***	1.363	1.227***	−0.274	1.201***	−1.115	1.341***	−1.264	1.168***	1.113
	(0.105)	(0.911)	(0.212)	(1.573)	(0.233)	(1.952)	(0.294)	(2.818)	(0.428)	(2.287)
Tgt Org Cap Stock	−0.688	−0.158	1.058*	0.080	0.155	0.208	0.211	0.521	−0.782*	0.990*
	(0.659)	(0.317)	(0.547)	(0.401)	(0.200)	(0.728)	(0.333)	(0.568)	(0.458)	(0.513)
Tgt Total Intangibles Ratio [OA–22]	0.176	0.802	1.127	2.547**	1.607	0.879	1.731	1.923	2.574**	1.870
	(1.448)	(2.275)	(2.479)	(1.090)	(1.026)	(1.844)	(1.118)	(2.124)	(1.204)	(1.207)

Tgt Tangibility [OA–22]	2.793	7.638	4.560	−0.089	0.586	−0.485	5.674**	−0.555	2.040	−0.228
	(3.371)	(5.811)	(4.406)	(1.371)	(2.036)	(1.809)	(2.167)	(1.992)	(2.888)	(1.566)
Tgt Market-to-Book [OA–22]	−0.056	0.091	−0.074***	0.035	0.025	−0.011	0.021	−0.038	−0.021	0.059
	(0.042)	(0.074)	(0.028)	(0.065)	(0.040)	(0.101)	(0.042)	(0.083)	(0.046)	(0.078)
Deal Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Acquiring Firm Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Acq Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tgt Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162	162	195	574	451	318	286	483	273	478
Adjusted R^2	0.301	0.117	0.381	0.078	0.126	0.093	0.206	0.084	0.184	0.109

(Table 7 continued)

the Fama-French 5 industry classification in either hightech (HT) or healthcare (HC), and 0 (No) otherwise. I hypothesize that the coefficient is positive and highly significant in these industries, which is supported, as shown in columns (7) and (8).

Lastly, since it is inherently difficult to quantify the secret value of a single trade secret, there exists at least a possibility to gauge the degree to which firms are relying on them. Following Glaeser (2018), I define *Tgt Trade Secrecy Mention Count in 10-K* as the number of mentions of either "trade secret", "trade secrets" and/or "trade secrecy" in target firm's most recent 10-K report filed with the SEC prior to offer announcement. Firms that use these words frequently are hypothesized to heavily rely on them, and often mention trade secrets in the context of discussing measures they take to protect them. Follwing that notion, I expect the effect to be stronger for firms that mention it more than once in their 10-Ks, since further investigation of these filings revealed that in some cases the word "trade secret" or a wildcard is used in headlines only. The last columns in Table 7, (9) and (10), clearly underpin this reasoning. The coefficient is positive and statistically highly significant only if the word group is used more than once (specification (9)), but also positive, yet insignificant in regression (10).

5.2 Different Scaling and Economic Magnitude

As a robustness, I scale all deal-level and intangible capital stock variables with *Deal Value* instead of target's market capitalization. For brevity, the table is deferred to the Appendix (Table A5). The number of observations slightly decreases due to the availability of valid data for acquirer's financial constraints indices. I do this to show that the inferences I draw in this paper are robust to different scaling methods[52]. The regressions deviate from each other only in the variables included to control for acquirer's financial constraints. Marginal effects are comparable to the baseline specifications in Table 2.

Table 8 regresses the pure dollar value of the BTF on capital stock measures and other deal-level variables in various specifications with and without deal advisor fees, with and without deal-level dummy variables, and a distinction of target's other total intangibles (regression

[52] In untabulated regressions, I additionally scale all capital stocks and termination fees by all off- and on-balance sheet assets, i.e., by the sum of knowledge, organizational, and total assets.

(4))[53]. The intuition behind this table is to receive a real dollar value for the economic magnitude of the claimed relation between target's knowledge capital stock value and *BTF size*. The full specification (column (4)) suggests that, on average, for every dollar worth of target firm's R&D capital stock, 16.3 cents of protective share is priced in the BTF, controlling for all other factors affecting *BTF size* in this paper. This final result emphasizes the economic relevance of bidder termination fees as incentive-compatible contract clauses in M&A negotiations.

Table 8

Robustness – Unscaled U.S. Dollar Values

Table 8 shows the results of linear fixed effects regressions of *BTF Size $_{Dollar\ Value}$* on *Tgt Know Cap Stock $_{Dollar\ Value}$* and all control variables used in the baseline regression in Table 2, column (3). The only difference is, that in this table, all key variables (*BTF Size*, *Tgt Know Cap Stock*, *Tgt Org Cap Stock*, *TTF Size*, *Acq All Financial Advisor Fees*, and *Tgt All Financial Advisor Fees*) are not scaled, i.e., are "pure" U.S. dollar values. Regressions (1)–(3) vary by the inclusion of Financial Advisor Fees, in regression (3), I split target firm's total intangibles into the two main components: goodwill and identifiable intangibles. Regression (4) adds all other controls as a robustness check. All regressions include *Acquirer Industry* × *Year Fixed Effects*, *Target Industry Fixed Effects* as well as an intercept but are unreported. All standard errors (in parentheses) are adjusted for heteroskedasticity (White (1980)) and within-cluster correlation. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	BTF Size $_{Dollar\ Value}$			
Independent Variables	(1)	(2)	(3)	(4)
Target Firm Characteristics				
Tgt Know Cap Stock $_{Dollar\ Value}$	0.155***	0.150***	0.170***	0.163***
	(0.043)	(0.050)	(0.045)	(0.042)
Tgt Org Cap Stock $_{Dollar\ Value}$	−0.007	0.000	−0.011	−0.008
	(0.027)	(0.031)	(0.030)	(0.027)
Tgt Total Intangibles $_{[OA–22]}$	0.005	0.002		
	(0.014)	(0.017)		
Tgt Goodwill $_{[OA–22]}$			0.018	0.015
			(0.016)	(0.014)
Tgt Identifiable Intangibles $_{[OA–22]}$			−0.011	−0.013
			(0.038)	(0.035)
Tgt Net PPE $_{[OA–22]}$	−0.002	−0.002	−0.008	−0.009
	(0.010)	(0.012)	(0.008)	(0.008)
Tgt Market-to-Book $_{[OA–22]}$				−4.346
				(3.617)
Deal Characteristics				
Tgt Initiation				−31.234**
				(14.351)
Auction				6.677
				(11.392)
TTF $_{Dollar\ Value}$	0.633*	0.638	1.072*	1.062*
	(0.373)	(0.401)	(0.570)	(0.539)
Deal Value	−1.025	−0.918	−16.951	−16.110
	(7.958)	(8.894)	(13.904)	(12.912)

[53] Observations drop from 769 to 729 given that some firms do not differentiate between goodwill and other identifiable intangible assets, and only report total intangibles instead.

	(1)	(2)	(3)	(4)
Friendly				−19.836
				(54.088)
Cash Only				2.035
				(11.223)
Tender Offer				−5.610
				(11.997)
Horizontal Takeover				3.879
				(13.490)
Relative Size Market Cap $_{[OA–22]}$				0.055*
				(0.029)
Post Closing Highly Conc Industry				30.632
				(28.404)
Acq All Financial Advisor Fees $_{\text{Dollar Value}}$	5.658***		4.711***	4.568***
	(2.077)		(1.736)	(1.644)
Tgt All Financial Advisor Fees $_{\text{Dollar Value}}$	−3.972**		−3.040**	−2.405
	(1.647)		(1.483)	(1.504)
Acquiring Firm Characteristics				
Acq Market Cap $_{[OA–22]}$	−0.535**	−0.636**	−0.468*	−0.426
	(0.250)	(0.276)	(0.250)	(0.315)
ln Acq 1YR Stock Return Volatility $_{[OA–1]}$				27.056
				(23.919)
Acq Market Leverage $_{[OA–22]}$				−5.280
				(43.827)
Acq Dividend Payer				−13.747
				(9.244)
Acq Market-to-Book $_{[OA–22]}$				−1.813
				(1.544)
Acq Industry × Year FE	Yes	Yes	Yes	Yes
Tgt Industry FE	Yes	Yes	Yes	Yes
Observations	769	769	729	729
Adjusted R^2	0.557	0.532	0.570	0.583

(Table 8 continued)

5.3 *Relation between Knowledge Capital Stock and Patenting Activity*

As developed in Ewens et al. (2020), intangible stocks are important production factors for intellectual capital in the form of patents. To show that my results are consistent with theirs, I also regress Kogan's et al. (2017) patent valuation measures obtained from market reactions to patent grants on *Tgt Know Cap Stock*, *Tgt Org Cap Stock*, and controls for already acquired intangibles and firm size. The results are shown in Table 9, suggesting that only *Tgt Know Cap Stock* is a significant driver of patent production in all specifications. All variables are scaled by total assets, given that firm size is a significant factor affecting the number and value of patents. All x-variables are lagged one year and logged. The inclusion of knowledge stocks significantly increases the within-R^2 (up to three to ten times), indicating that they explain a meaningful amount of variation in both patent valuation and patent count. As argued in Kogan et al. (2017), the distinction into market and scientific values is important,

Table 9

Robustness – Relation between Target Firm's Patents and Knowledge Capital Stock

This table presents the results of linear fixed effects regressions of measures of target firm's patents on target firm's knowledge capital stock. The dependent variable in regressions (1)–(3) is *ln Target Patent Value (market-weighted)*, the natural logarithm of target firm's market-weighted patent value, the dependent variable in regressions (4)–(6) is *ln Target Patent Value (citation-weighted)*, the natural logarithm of target firm's citation-weighted patent value, both obtained from Kogan et al. (2017) and their data website. *ln Target Patent Count (recently granted)* is the number of patents recently (i.e., in the whole fiscal year prior to offer announcement) granted to the target firm, and *ln Target Patent Count (total stock)* is the total number of patents the target firm are granted until the fiscal year end prior to offer announcement, i.e., yearly counts of target firm's granted United States Patent and Trademark Office (USPTO) patents. Patents must not be expired in order to be included in *ln Target Patent Count (total stock)*. The data on total stocks are obtained from the University of Virginia (UVA) Darden Global Corporate Patent Dataset (https://patents.darden.virginia.edu/get-data (permanent link)). All variables are scaled by target firm's total assets and logged, all explanatory variables are also lagged one year. All regressions include *Target Industry × Year Fixed Effects* as well as an intercept but are unreported. All standard errors (in parentheses) are adjusted for heteroskedasticity (White (1980)) and within-cluster correlation. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Target Patent Value						Target Patent Count					
Dependent Variable	ln Target Patent Value (market-weighted)			ln Target Patent Value (citation-weighted)			ln Target Patent Count (recently granted)			ln Target Patent Count (total stock)		
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lag ln Tgt Know Cap Stock		0.134***	0.122**		0.227***	0.174**		0.142***	0.122***		0.172***	0.163***
		(0.039)	(0.051)		(0.081)	(0.072)		(0.035)	(0.026)		(0.033)	(0.032)
Lag ln Tgt Org Cap Stock			0.024			0.103			0.039			0.021
			(0.037)			(0.081)			(0.026)			(0.037)
Lag ln Tgt Total Intangibles	−0.038	0.026	0.025	−0.243*	−0.135	−0.141	−0.102**	−0.034	−0.036	−0.075**	−0.000	−0.001
	(0.061)	(0.064)	(0.064)	(0.134)	(0.151)	(0.147)	(0.035)	(0.035)	(0.032)	(0.031)	(0.024)	(0.023)
Lag ln Tgt Sales	−0.086*	−0.070	−0.085	−0.069	−0.040	−0.108**	−0.003	0.015	−0.011	−0.018	0.001	−0.010
	(0.045)	(0.042)	(0.054)	(0.052)	(0.053)	(0.052)	(0.021)	(0.019)	(0.018)	(0.018)	(0.016)	(0.015)
Tgt Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	158	158	158	158	158	158	158	158	158	246	246	246
Adjusted R^2	0.012	0.055	0.051	0.027	0.085	0.096	0.055	0.280	0.299	0.033	0.364	0.367
Within R^2	0.025	0.073	0.076	0.040	0.102	0.119	0.067	0.294	0.317	0.041	0.372	0.378

because a patent may represent only a small scientific advance, yet generate large profits and thus private returns to the firm through restricting competition. The obtained coefficients are similar to Ewens et al. (2020), with a 1% increase in target's knowledge capital stock resulting in a 0.122% increase in patent market value, on average[54]. Figure A2 in the Appendix plots the respective bivariate relations between targets' patent values, patent count, and knowledge capital stocks.

5.4 Relation between Knowledge Capital Stock and Mentioning Trade Secrets in 10-Ks

Based on the inferences drawn in the preceding subsection, it is also obvious to assume that there should exist a relation between knowledge capital value and the existence of trade secrets. Albeit one cannot directly observe and confirm the presence of trade secrets within a firm, one can at least infer that they likely exist if they are mentioned in official reports. Therefore, as outlined in the paragraph above, I parse the most recent 10-K report of the target firm prior to offer announcement by searching the word group "trade secret" or a respective wildcard. Firms that often mention trade secrets in their SEC reports are hypothesized to rely on them[55], and often describe and discuss safety mechanisms established in the firm to protect them. Table 10 shows the results for logit and linear fixed effects regressions of a dummy coded 1 if trade secrets are mentioned (specification (1)) as well as the number of mentions (continuous measure, specification (2)) on target's knowledge capital stock value, scaled by total assets for comparison. In both regressions, the coefficient is positive and statistically highly significant. In the logit model, I include x-standardized odds ratios [in angular parentheses] that relate to the change in the probability of including the word group "trade secre*" for a one-standard deviation increase in the independent variable. Thus, a one-standard deviation increase from the sample mean of *Tgt Know Cap Stock* $_{[TA]}$ increases the odds of mentioning trade secrets in the 10-K report by the factor of 25, on average. Also, firms that mention them seem to have low leverage and are younger firms, confirming the results of Glaeser (2018).

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[54] The results hold if all variables are scaled by target firm's market capitalization instead of total assets. The number of observations drops to 158 and 246, respectively, given that the data from Kogan et al. (2017) cover firms until 2010 (regressions (1)–(9)) and firms that have valid data on patent total stocks obtained from the UVA Darden Global Corporate Patent Dataset (regressions (10)–(12)).

[55] Although mentioning them in 10-Ks do not make them legally enforceable (especially in lawsuits against misappropriation), it is obvious that they fulfill at least a highly indicative function.

Table 10

Robustness – Determinants of Disclosure-based Mentions of Target Firm's Trade Secrets

This table depicts the results of logit (1) and linear (2) fixed effects regressions of proxies of target firm's trade secrecy on target firm's knowledge capital stock and other controls. The dependent variable in specification (1) is the dummy variable *Tgt Trade Secrets Mentioned in 10-K* which equals 1 if the word group "trade secret" or a wildcard [*] are mentioned in target firm's most recent 10-K report filed with the SEC prior to offer announcement. In specification (2), the dependent variable, *Tgt Trade Secrecy Mention Count in 10-K*, is the exact count, i.e., how many times the word groups are mentioned. The first four independent variables with the index [TA] are scaled by target firm's total assets and are lagged one year. Target firm's stock return volatility, market-to-book, and market leverage are defined as for the acquiring firm and measured 42 trading days prior to the 10-K report date. All regressions include *Target Industry Fixed Effects* and *Year Fixed Effects* as well as an intercept but are unreported. All standard errors (in parentheses) are adjusted for heteroskedasticity (White (1980)) and within-cluster correlation. Model (1) includes x-standardized odds ratios [in angular parentheses] that relate to the change in the probability of including the word group "trade secre*" for a one-standard deviation increase in the independent variable. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Tgt Trade Secrets Mentioned in 10-K	Tgt Trade Secrecy Mention Count in 10-K
Independent Variables	(1)	(2)
Tgt Know Cap Stock $_{[TA]}$	14.244*** (3.828) [24.728]	2.182*** (0.489)
Tgt Org Cap Stock $_{[TA]}$	−0.131 (0.388) [0.948]	−0.170 (0.294)
Tgt Total Intangibles $_{[TA]}$	3.939*** (0.835) [2.130]	1.210** (0.578)
Tgt Sales $_{[TA]}$	0.097 (0.238) [1.073]	−0.618*** (0.146)
ln Tgt 1YR Stock Return Volatility $_{[10\text{-}K\text{-}Date\text{-}42]}$	0.632 (0.467) [1.384]	0.698** (0.274)
Tgt Market-to-Book $_{[10\text{-}K\text{-}Date\text{-}42]}$	−0.016 (0.047) [0.954]	0.057* (0.032)
Tgt Market Leverage $_{[10\text{-}K\text{-}Date\text{-}42]}$	−3.010** (1.282) [0.653]	−1.990*** (0.745)
Tgt Firm Age	−0.010** (0.004) [0.670]	−0.006*** (0.002)
Tgt Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	522	522
Pseudo R^2	0.579	
Adjusted R^2		0.395

Figure A3 in the Appendix additionally plots the predicted probabilities of mentioning trade secrets against *Tgt Know Cap Stock* $_{[TA]}$, visualizing the strong positive association (steeply increasing S-shape of the fitted function).

5.5 *Degree of Information Diffusion from Target to Acquirer*

Although it is not possible to directly assess the degree to which the negotiating firms "qualitatively" exchange information, i.e., how intense negotiations proceed, it is at least possible to proxy for the quantitative component. In an additional test in Table 11, I include deal length measures for both the private takeover process only (regressions (1)–(3)), as well as the whole takeover process, including the public phase (columns (4)–(6)). The start dates are manually parsed from the background sections of the merger agreements filed with the SEC. I define three different start dates for private negotiations between acquirer and target: first, *Kick-Off date* refers to the first date the target and an interested party (i.e., the deal announcing acquirer or a third party) get in contact with each other on deal related matters. This date marks the first date of the coherent private takeover process. Second, *First Board Meeting date* refers to the date when the first board meeting on deal related matters between the deal announcing acquirer and target management board takes place. Third, *Confidentiality Agreement date* refers to the date when the deal announcing acquirer signs a confidentiality (non-disclosure) agreement with the target firm.

As depicted in Table 11, only the deal lengths starting at the confidentiality agreement date are positively and highly statistically significantly related to *BTF size*, suggesting that these measures capture the period in which significant information flows between the parties, and especially from the target to the prospective acquirer. *Any Pre-Contact with Acq* is a dummy variable that equals 1 if the background section of the merger agreement mentions any contact between the final bidding acquirer and target prior to the start of the coherent private takeover process, and 0 otherwise, and is positive and statistically significant at the 5% level in all specifications. Given that one can hypothesize that this acquirer has collected more information about the target, all else equal, this is what one would expect. Including these deal-level controls do not change the inference over and significance of *Tgt Know Cap Stock*.

Table 11

Robustness – Measures of the Length of the Private Takeover Process

Table 11 presents the results of linear fixed effects regressions of *BTF Size* on *Tgt Know Cap Stock* and different measures of deal length (all measured in months). *Private Takeover Process Lengths Only* shows three different deal length measures with different start dates which are all measured until the announcement date (AD) of the deal. *Whole Takeover Process Lengths* depicts three different deal length measures with the same three different starting dates as described above, but are now all measured until the resolution date (RD) of the deal, i.e., the date where the deal was either successfully closed or withdrawn. The sample size is reduced from 769 to 398 observations in order to form a sample where I am able to collect all dates for respective deal length measures. All standard errors (in parentheses) are adjusted for heteroskedasticity (White (1980)) and within-cluster correlation. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	BTF Size					
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Tgt Know Cap Stock	1.466***	1.466***	1.543***	1.428***	1.429***	1.483***
	(0.216)	(0.215)	(0.222)	(0.213)	(0.213)	(0.217)
Any Pre-Contact with Acq	1.033**	1.019**	0.934**	1.108**	1.090**	0.981**
	(0.439)	(0.429)	(0.434)	(0.441)	(0.434)	(0.436)
Private Takeover Process Lengths Only						
Kick-Off vs. AD	0.029					
	(0.089)					
First Board Meeting vs. AD		0.011				
		(0.080)				
Confidentiality Agreement vs. AD			0.162**			
			(0.066)			
Whole Takeover Process Lengths						
Kick-Off vs. RD				0.093*		
				(0.052)		
First Board Meeting vs. RD					0.080*	
					(0.048)	
Confidentiality Agreement vs. RD						0.144***
						(0.043)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Acq Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Tgt Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	398	398	398	398	398	398
Adjusted R^2	0.202	0.202	0.222	0.211	0.209	0.232

Despite the fact that private targets are not obliged to file merger documents with the SEC, and many do not even disclose R&D expenditures – are hence not part of the sample in this paper, I claim my results to also hold for private transactions, as the possibility to include termination fee provisions in M&A contracts does not depend on the associated firm's listing status.

6 Conclusion

This paper establishes a robust link between target firms' intellectual property value and the size of negotiated bidder termination fees (BTFs) in M&A contracts, that provide targets with a compensation payment for revelation of secret information if acquirers abandon deals due to reasons under their control. Applying Ewens' et al. (2020) model to estimate the capitalized value of target firm's intangible stocks, my findings suggest that, on average, for every dollar of target firm's R&D capital stock, roughly 16 cents of protective share is incorporated in the BTF, controlling for a wide array of factors deemed to affect BTF size. This relation is economically significant.

By utilizing an instrumental variables approach that exploits non-deal-related exogenous variation, I am able to show that my results are robust to endogeneity concerns. The relation between target's R&D intensity and the size of the BTF is more pronounced, if the target invests heavily in R&D, is a pioneer in its technology space, produces unique products, belongs to the hightech or healthcare industry, and frequently uses the term "trade secret" or a wildcard in its 10-K report filed with the SEC prior to deal announcement. The effect is moreover increasing in the degree of technological proximity as well as product market rivalry between the acquirer-target firm pair, suggesting that new innovation, generated through R&D, can be most valuable for firms with a similar technology base and firms that are also direct competitors. An event study at deal resolution indicates that target returns are increasing in the size of the BTF if acquirers abandon deals and pay the fee, underlining the compensating character of bidder termination fees.

Taken together, this paper suggests that BTFs serve as a contract mechanism that provide target firms compensation for revelation of sensitive information in M&A negotiations if acquirers terminate deals. These fees thereby increase targets' incentives to reveal these information and increase acquirers' incentives to close the deal.

Valuing intangible assets, especially in the form of private trade secrets, remains a inherently difficult phenomenon to study empirically. This paper hightlights the increasing importance of intellectual property in M&A negotiations, not only for practitioners, but also for future finance research.

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8 Appendix

Appendix – Table A1

Variable Definitions

Table A1 presents the definitions of all variables used throughout this paper, including the source.

Variable	Definition
Panel A: Termination Fees and Target Intangible Capital Stocks	
BTF Dummy	Dummy variable that equals 1 if the merger agreement includes a bidder termination fee provision, and 0 otherwise (*Source: SEC Merger Filings*).
TTF Dummy	Dummy variable that equals 1 if the merger agreement includes a target termination fee provision, and 0 otherwise (*Source: SEC Merger Filings*).
$BTF_{\text{Dollar Value}}$	USD (mm) amount of the bidder termination fee (*Source: SEC Merger Filings*).
$TTF_{\text{Dollar Value}}$	USD (mm) amount of the target termination fee (*Source: SEC Merger Filings*).
BTF Size	USD (mm) amount of the bidder termination fee divided by the market capitalization (also in USD mm) of the target firm 42 trading days prior to offer announcement and expressed in percentage points (*Source: SEC Merger Filings, S&P Capital IQ*).
TTF Size	USD (mm) amount of the target termination fee divided by the market capitalization (also in USD mm) of the target firm 42 trading days prior to offer announcement and expressed in percentage points (*Source: SEC Merger Filings, S&P Capital IQ*).
$BTF\ Size_{\text{Deal Value}}$	USD (mm) amount of the bidder termination fee divided by *Deal Value* (also in USD mm) and expressed in percentage points (*Source: SEC Merger Filings, Thomson Reuters SDC Platinum*).
$TTF\ Size_{\text{Deal Value}}$	USD (mm) amount of the target termination fee divided by *Deal Value* (also in USD mm) and expressed in percentage points (*Source: SEC Merger Filings, Thomson Reuters SDC Platinum*).
$Tgt\ Know\ Cap\ Stock_{\text{Dollar Value}}$	Knowledge Capital Stock (in USD mm) in the target firm, defined as accumulated and depreciated R&D expenses in the target firm over the last 10 fiscal years before offer announcement, using the perpetual inventory method: $$G_{i,t} = \sum_{k=1}^{10} (1-\delta_G)^k \ R\&D_{i,t-k}$$ where δ_G is the intangible depreciation rate of R&D. I use the industry-specific estimates for δ_G obtained in Ewens et al. (2020) (*Source: Compustat*).
$Tgt\ Org\ Cap\ Stock_{\text{Dollar Value}}$	Organizational Capital Stock (in USD mm) in the target firm, defined as accumulated and depreciated SG&A expenses in the target firm over the last 10 fiscal years before offer announcement, using the perpetual inventory method: $$S_{i,t} = \sum_{k=1}^{10} (1-\delta_S)^k \ \gamma \ SG\&A_{i,t-k}$$ where δ_S is the intangible depreciation rate (set to $\delta_S = 20\%$ following the literature consensus, see, e.g., Li, Qiu, and Shen (2018) and Falato, Kadyrzhanova, Sim, and Steri (2020)) and γ the fraction of SG&A to be capitalized. I use the industry-specific estimates for γ obtained in Ewens et al. (2020). I further measure SG&A net of R&D expense and Research and Development in Process (*Source: Compustat*).
Tgt Know Cap Stock	*Tgt Know Cap Stock* divided by the market capitalization (also in USD mm) of the target firm 42 trading days prior to offer announcement (*Source: Compustat, S&P Capital IQ*).
Tgt Org Cap Stock	*Tgt Org Cap Stock* divided by the market capitalization (also in USD mm) of the target firm 42 trading days prior to offer announcement (*Source: Compustat, S&P Capital IQ*).
$Tgt\ Know\ Cap\ Stock_{\text{Deal Value}}$	*Tgt Know Cap Stock* divided by *Deal Value* (also in USD mm).
$Tgt\ Org\ Cap\ Stock_{\text{Deal Value}}$	*Tgt Org Cap Stock* divided by *Deal Value* (also in USD mm).

Tgt 5YR Avrg Yearly Know Cap Growth	Average annualized growth rate of *Tgt Know Cap Stock* within the target firm calculated over the last five fiscal years prior to offer announcement.
Tgt Know Cap Intensity	*Tgt Know Cap Stock* divided by the sum of *Tgt Know Cap Stock* and *Tgt Org Cap Stock*: $$\textit{Tgt Know Cap Intensity} = \frac{\textit{Tgt Know Cap Stock}}{\textit{Tgt Know Cap Stock} + \textit{Tgt Org Cap Stock}}$$

Panel B: Deal and Industry Characteristics, and Measures of Technological Proximity and Product Market Rivalry

Tgt Initiation	Dummy variable that equals 1 if the target initiated the deal, and 0 otherwise (*Source: SEC Merger Filings*).
Auction	Dummy variable that equals 1 if the private sales process is characterized as an auction, and 0 otherwise. As in Boone and Mulherin (2008), I classify the private sales process as an auction, if the target signs confidentiality agreements with more than one prospective acquirer. To the contrary, I classify the sales process as a (1:1) negotiation, if the target firm focuses on a single acquirer throughout the whole private takeover phase, i.e., negotiations are deals with one formal contact, one signed confidentiality agreement, and one private (and later public) bid for the target by the original acquirer (*Source: SEC Merger Filings*).
Deal Value	USD (bn) value of the transaction, i.e., total transaction value excluding assumed liabilities (*Source: Thomson Reuters SDC Platinum*).
Friendly	Dummy variable that equals 1 if the deal attitude is friendly on the announcement day of the deal, and 0 otherwise (*Source: S&P Capital IQ*).
Cash Only	Dummy variable that equals 1 if the payment by the acquirer is made entirely in cash, and 0 otherwise (*Source: Thomson Reuters SDC Platinum*).
Tender Offer	Dummy variable that equals 1 if the deal is classified as a tender offer, and 0 otherwise (*Source: SEC Merger Filings*).
Horizontal Takeover	Dummy variable that equals 1 if both the acquiring and the target firm are primarily assigned to the same industry as defined by all four SIC digits, and 0 otherwise (*Source: S&P Capital IQ*).
Relative Size Market Cap $_{[OA-22]}$	*Acq Market Cap* $_{[OA-22]}$ divided by *Tgt Market Cap* $_{[OA-22]}$.
Post Closing Industry HHI	Value of the Herfindahl-Hirschman Index (HHI) of the primary industry the acquirer is operating in after completing the planned deal and calculated for horizontal takeovers only. The HHI is calculated every fiscal year by summing the squared market shares of each firm in the respective SIC4 industry based on the firms' reported gross sales. *Post Closing Industry HHI* is equal to zero for non-horizontal deals (*Source: Compustat*).
Post Closing Industry HHI Increase	Merger-induced change in SIC4 industry HHI, i.e., increase in concentration through the combination of both the acquiring and target firms' sales. The increase in the HHI is equal to twice the product of the market shares of the merging firms (*Source: Compustat*).
Post Closing Highly Conc Industry	Dummy variable that equals 1 if the planned deal results in the SIC4 industry HHI (*Post Closing Industry HHI*) exceeding 0.25, and 0 otherwise. The U.S. Department of Justice (DoJ) and the Federal Trade Commission (FTC) define an industry as a highly concentrated market if the HHI increases beyond 0.25.
Acq All Financial Advisor Fees $_{\text{Dollar Value}}$	Imputed USD (mm) value of acquirer financial advisor fees irrespective of the deal outcome, i.e., directly assignable out-of-pocket expenses (*Source: Thomson Reuters SDC Platinum*).
Tgt All Financial Advisor Fees $_{\text{Dollar Value}}$	Imputed USD (mm) value of target financial advisor fees irrespective of the deal outcome, i.e., directly assignable out-of-pocket expenses (*Source: Thomson Reuters SDC Platinum*).
Acq All Financial Advisor Fees $_{\text{Deal Value}}$	*Acq All Financial Advisor Fees* $_{\text{Dollar Value}}$ scaled by *Deal Value*.
Tgt All Financial Advisor Fees $_{\text{Deal Value}}$	*Tgt All Financial Advisor Fees* $_{\text{Dollar Value}}$ scaled by *Deal Value*.

Technological Proximity (Tech Prox)	*Technological Proximity (Tech Prox)* is calculated by applying the Mahalanobis generalization method introduced in Bloom, Schankerman, and Van Reenen (2013) to the Jaffe (1986) proximity measure. The measure describes the correlation of patenting across United States Patent and Trademark Office (USPTO) technology classes between pairs of firms (i.e., acquirer-target pairs in the sample). First, all of the firm's patents between 1970 and 2006 are allocated into the different 426 USPTO technology classes, defining the scope-of-innovation-activity-vector $T_i = (T_{i1}, T_{i2}, T_{i3}, ..., T_{i426})$ for firm i where $T_{i\tau}$ is the share of firm i's patents in technology class τ, i.e., $T_{i\tau}$ is the ratio of the number of awarded patents to firm i in technology class τ to the total number of awarded patents in all technology classes over the whole period since 1970. Specifically, technological proximity between acquirer (Acq) and target (Tgt) is defined as the following correlation coefficient: $$Tech\ Prox_{Acq,Tgt} = \frac{T_{Acq}T^{'}_{Tgt}}{\sqrt{T_{Acq}T^{'}_{Acq}}\sqrt{T_{Tgt}T^{'}_{Tgt}}}$$ The applied Mahalanobis distance metric extension allows for spillovers between different technology classes, which is ruled out by the Jaffe (1986) metric (which assumes full spillovers within the same class and nothing otherwise). In summary, Mahalanobis measures cross technology class spillovers by using revealed preference. If two technologies are often located together in the same firm (e.g., "computer input/output" and "computer processing") then they infer the distance between the technologies to be smaller, so spillovers will be greater. They proxy this by the share of times the two technology classes are patented within the same firm. See Lucking, Bloom, and Van Reenen (2018) for the extended description and notation. I apply the STATA™ code available on Nicholas Bloom's website (https://nbloom.people.stanford.edu/research) to generate the spillover-adjusted correlation coefficient *Technological Proximity (Tech Prox)*.
Product Market Similarity (PMS) $_{TNIC1}$	Yearly firm-by-firm pairwise product market similarity score (*PMS*, real number in the interval [0,1]) calculated for each firm-firm-fiscal-year combination by parsing the product descriptions from the firms' annual 10-Ks and forming word vectors for each firm to compute continuous measures of product similarity for every pair of firms in the sample in each year (a pairwise similarity matrix). A higher score relates to higher word similarity (i.e., the text of the two firms' business descriptions has more common vocabulary than a pair of firms with a lower score), used as a proxy for product similarity and thus product-market rivalry, i.e., firm pairs with a higher score are "nearer" rivals. A score near zero indicates that the given pair of firms use effectively unrelated product market text. All Text-based Network Industry Classifications (TNIC1) data obtained from the Hoberg-Phillips Data Library (Hoberg and Phillips (2010, 2016): http://hobergphillips.tuck.dartmouth.edu/). TNIC1 is the highest possible granularity: the score is calculated for every firm-firm-fiscal-year combination during the 1996-2017 period for publicly traded firms (U.S. domestic firms traded on either NYSE, AMEX, or NASDAQ) with a valid GVKEY in Compustat that filed 10-K reports with the SEC at the respective fiscal year end and with valid data in CRSP. The data are then mapped to the M&A sample by using an algorithmically generated one-to-one mapping method with AcqGVKEY-TgtGVKEY-FiscalYear for each individual transaction.
Product Market Similarity (PMS) $_{TNIC2}$	Calculated in the same way as *Product Market Similarity (PMS)* $_{TNIC1}$, but calibrated to match the granularity of two-digit SIC codes. All Text-based Network Industry Classifications (TNIC2) data obtained from the Hoberg-Phillips Data Library (Hoberg and Phillips (2010, 2016): http://hobergphillips.tuck.dartmouth.edu/).
Product Market Similarity (PMS) $_{TNIC3}$	Calculated in the same way as *Product Market Similarity (PMS)* $_{TNIC1}$, but calibrated to match the granularity of three-digit SIC codes. All Text-based Network Industry Classifications (TNIC3) data obtained from the Hoberg-Phillips Data Library (Hoberg and Phillips (2010, 2016): http://hobergphillips.tuck.dartmouth.edu/).
Acq Induced Cancellation	Dummy variable that equals 1 if the acquirer induced the cancellation of the deal, and 0 otherwise (*Source: Official Press Releases*).
Third Party Competing Bid Cancellation	Dummy variable that equals 1 if the deal was cancelled due to a third party bid for the target that led to the cancellation of the original bid, and 0 otherwise (*Source: Official Press Releases*).

Deal Completion	Dummy variable that equals 1 if the deal was closed successfully, and 0 if cancelled (*Source: S&P Capital IQ*).
Kick-Off vs. AD	Length of the private takeover process, starting at the *Kick-Off date* until announcement date (AD) of the deal and measured in months. *Kick-Off date* refers to the first date the target and an interested party (i.e., the deal announcing acquirer or a third party) get in contact with each other on deal related matters. This date marks the first date of the coherent private takeover process (*Source: SEC Merger Filings, S&P Capital IQ*).
First Board Meeting vs. AD	Length of the private takeover process, starting at the *First Board Meeting date* until announcement date (AD) of the deal and measured in months. *First Board Meeting date* refers to the date where the first board meeting on deal related matters between the deal announcing acquirer and target management board takes place (*Source: SEC Merger Filings, S&P Capital IQ*).
Confidentiality Agreement vs. AD	Length of the private takeover process, starting at the *Confidentiality Agreement date* until announcement date (AD) of the deal and measured in months. *Confidentiality Agreement date* refers to the date where the deal announcing acquirer signs a confidentiality (non-disclosure) agreement with the target firm (*Source: SEC Merger Filings, S&P Capital IQ*).
Kick-Off vs. RD	Defined as *Kick-Off vs. AD* but instead measured until resolution date (RD) of the deal, i.e., the date where the deal was either successfully closed or withdrawn: *Kick-Off vs. RD = Kick-Off vs. AD + Public Takeover Length*.
First Board Meeting vs. RD	Defined as *First Board Meeting vs. AD* but instead measured until resolution date (RD) of the deal, i.e., the date where the deal was either successfully closed or withdrawn: *First Board Meeting vs. RD = First Board Meeting vs. AD + Public Takeover Length*.
Confidentiality Agreement vs. RD	Defined as *Confidentiality Agreement vs. AD* but instead measured until resolution date (RD) of the deal, i.e., the date where the deal was either successfully closed or withdrawn: *Confidentiality Agreement vs. RD = Confidentiality Agreement vs. AD + Public Takeover Length*.
Any Pre-Contact with Acq	Dummy variable that equals 1 if the background section of the merger agreement mentions any contact between the final bidding acquirer and target prior to the start of the coherent private takeover process, and 0 otherwise (*Source: SEC Merger Filings*).

Panel C: Acquiring Firm Characteristics	
Acq Market Cap $_{[OA-22]}$	Last sale price of acquiring firm's stock (adjusted for stock splits) multiplied with the latest number of shares outstanding, measured 22 trading days prior to offer announcement and expressed in billions of USD (*Source: S&P Capital IQ*).
Acq Market-to-Book $_{[OA-22]}$	Market-to-book ratio of acquirer's stock, calculated as *Acq Market Cap $_{[OA-22]}$* divided by the latest available value of total common equity (= common stock & additional paid in capital + retained earnings + treasury stock & other) 22 trading days prior to offer announcement (*Source: S&P Capital IQ*).
ln Acq 1YR Stock Return Volatility $_{[OA-1]}$	Natural logarithm of 1 plus the standard deviation of weekly log-normal price returns of the acquiring firm's stock over the year preceding the offer announcement, annualized with a factor of 52 for the 52 trading weeks in a year and measured one trading day prior to offer announcement (*Source: S&P Capital IQ*).
Acq Market Leverage $_{[OA-22]}$	Book value of total debt divided by the market value of the acquiring firm's total assets. Market value of total assets is calculated in the following way: *Acq Total Assets + Acq Market Cap $_{[OA-22]}$ − Acq Total Common Equity*, all measured 22 trading days prior to offer announcement. Total Common Equity is defined in the following way: common stock & additional paid in capital + retained earnings + treasury stock & other (*Source: S&P Capital IQ*).
Acq Dividend Payer	Dummy variable that equals 1 if the acquiring firm paid positive dividends on either common and/or preferred stock during the fiscal year preceding the offer announcement, and 0 otherwise (*Source: Compustat*).

Acq Hadlock-Pierce-Index	Measure for acquiring firm's financial constraints, proposed by Hadlock and Pierce (2010), and calculated in the following way: $\textit{Hadlock-Pierce-Index} = -0.737 \cdot \textit{Size} + 0.043 \cdot \textit{Size}^2 - 0.040 \cdot \textit{Age}$ where *Size* equals the natural logarithm of inflation-adjusted book assets (in USD mm), and *Age* is the number of years the firm is listed with a non-missing stock price on Compustat. In calculating this index, *Size* is winsorized (i.e., capped) at (the ln of) USD 4,500 million, and *Age* is winsorized at 37 years. All variables are measured at the last fiscal year end date prior to offer announcement (*Source: Compustat*).
Acq Whited-Wu-Index	Measure for acquiring firm's financial constraints, developed by Whited and Wu (2006), and calculated in the following way: $\textit{Whited-Wu-Index} = -0.091 \cdot CF - 0.062 \cdot DIVPOS + 0.021 \cdot TLTD - 0.044 \cdot LNTA + 0.102 \cdot ISG - 0.035 \cdot SG$ where *CF* is the ratio of cash flow to total assets (*CF* = (income before extraordinary items + depreciation and amortization) / total assets), *DIVPOS* is a dummy variable equal to 1 if the firm pays positive dividends on either common and/or preferred stock, 0 otherwise, *TLTD* is the ratio of total long term debt to total assets, *LNTA* is the natural logarithm of total assets (in USD mm), *ISG* is the firm's SIC3 industry sales growth, and *SG* is firm sales growth, whereas sales growth is the percentage growth relative to the preceding fiscal year. All variables are measured at the last fiscal year end date prior to offer announcement (*Source: Compustat*).
Acq Kaplan-Zingales-Index	Measure for acquiring firm's financial constraints, suggested by Kaplan and Zingales (1997), and calculated in the following way: $\textit{Kaplan-Zingales-Index} = -1.001909 \cdot CF - 39.3678 \cdot TDIV + 3.139193 \cdot TLTD - 1.314759 \cdot CASH + 0.2826389 \cdot Q$ where *CF* is the ratio of cash flow to total net property, plant, and equipment of the preceding fiscal year, Net PPE $_{t-1}$ (*CF* = (income before extraordinary items + depreciation and amortization) / Net PPE $_{t-1}$), *TDIV* is total dividends scaled by Net PPE $_{t-1}$, *TLTD* is the ratio of total long term debt to total capital (*TLTD* = (total long term debt + debt in current liabilities) / (total long term debt + debt in current liabilities + stockholders equity)), *CASH* is cash and short term investments scaled by Net PPE $_{t-1}$, and *Q* is firm's Tobin's Q (*Q* = (total assets + fiscal year end share price · number of shares outstanding − book value of common equity − deferred taxes) / total assets). All variables are measured at the last fiscal year end date prior to offer announcement (*Source: Compustat*).

Panel D: Target Firm Characteristics

Tgt Market Cap $_{[OA-42]}$	Last sale price of target firm's stock (adjusted for stock splits) multiplied with the latest number of shares outstanding, measured 42 trading days prior to offer announcement and expressed in millions of USD (*Source: S&P Capital IQ*).
Tgt Market-to-Book $_{[OA-22]}$	Defined as *Acq Market-to-Book* $_{[OA-22]}$, but instead measured for target firm's stock.
Tgt Total Assets $_{[OA-22]}$	Total Assets of the target firm measured 22 trading days prior to offer announcement (*Source: S&P Capital IQ*).
Tgt Total Intangibles $_{[OA-22]}$	Total Intangible Assets of the target firm measured 22 trading days prior to offer announcement (*Source: S&P Capital IQ*).
Tgt Goodwill $_{[OA-22]}$	Goodwill of the target firm measured 22 trading days prior to offer announcement (*Source: Compustat*).
Tgt Identifiable Intangibles $_{[OA-22]}$	Identifiable Intangible Assets of the target firm measured 22 trading days prior to offer announcement (*Source: Compustat*).
Tgt Net PPE $_{[OA-22]}$	Net Property, Plant, and Equipment of the target firm measured 22 trading days prior to offer announcement (*Source: S&P Capital IQ*).
Tgt Current Assets $_{[OA-22]}$	Current Assets of the target firm measured 22 trading days prior to offer announcement (*Source: Compustat*).
Tgt Total Intangibles Ratio $_{[OA-22]}$	*Tgt Total Intangibles* $_{[OA-22]}$ scaled by *Tgt Total Assets* $_{[OA-22]}$.

Tgt Goodwill Ratio $_{[OA-22]}$	*Tgt Goodwill* $_{[OA-22]}$ scaled by *Tgt Total Assets* $_{[OA-22]}$.
Tgt Identifiable Intangibles Ratio $_{[OA-22]}$	*Tgt Identifiable Intangibles* $_{[OA-22]}$ scaled by *Tgt Total Assets* $_{[OA-22]}$.
Tgt Tangibility $_{[OA-22]}$	*Tgt Net PPE* $_{[OA-22]}$ scaled by *Tgt Total Assets* $_{[OA-22]}$.
Tgt Current Assets Ratio $_{[OA-22]}$	*Tgt Current Assets* $_{[OA-22]}$ scaled by *Tgt Total Assets* $_{[OA-22]}$.
Tgt C4 CAR $_{RD\,[-3;+3]}$	Seven-trading-day cumulative abnormal return (in percentage points) of target firm's stock calculated using the Carhart (1997) four-factor model to model normal returns. The model parameters are estimated over the period −250 to −23 trading days (prior) to deal resolution date. Security prices are dividend adjusted day close prices, further adjusted for stock splits, cash dividends, rights offerings, and spin-offs (*Source: CRSP*).
Tgt Unique Product Industry	Dummy variable that equals 1 if the target firm's industry is in the top quartile of all Fama-French 49 industries annually sorted by industry-median product uniqueness, 0 otherwise, where product uniqueness is defined as all selling expenses scaled by sales. Calculated following Titman and Wessels (1988) and Masulis, Wang, and Xie (2007) (*Source: Compustat*).
Tgt FF5 HTHC Industry	Dummy variable that equals 1 if the target is assigned to the Fama-French 5 industry classification in either hightech (HT) or healthcare (HC), and 0 otherwise (*Source: Compustat*).
Tgt Patent Value (market-weighted)	Total USD (mm) value $\Theta^{sm}_{i,t}$ of innovation produced by the target firm in the fiscal year prior to offer announcement, by summing up all the values of patents ξ_j that were granted to the target firm (obtained from Kogan et al. (2017), and downloaded from their website: https://paper.dropbox.com/doc/U.S.-Patent-Data-1926-2010-t5nuN-WnTH1InM0gyxkizL): $$\Theta^{sm}_{i,t} = \sum_{j \in P_{i,t}} \xi_j \qquad \text{with} \qquad \xi_j = \frac{1}{(1-\overline{\pi})} \frac{1}{\mathrm{N}_j} E\left[\mathrm{v}_j \mid \mathrm{R}_j\right] \mathrm{M}_j$$ where $P_{i,t}$ denotes the set of patents issued to the target firm i in year t, $\overline{\pi}$ is the unconditional probability of a successful patent application ($\overline{\pi}$ is set to 56%, see Carley, Hedge, and Marco (2015)), v_j is the fraction of the idiosyncratic stock return R_j that is attributable to the patent grant, and M_j is the market capitalization of the target firm i that issued patent j on the trading day prior to the announcement of the patent issuance. If multiple patents N_j are issued to the same firm on the same patent issuance announcement day as patent j, each patent is assigned a fraction $1/\mathrm{N}_j$. If the target firm i is issued no patent in year t, the variable $\Theta^{sm}_{i,t}$ is set to 0 (see Kogan et al. (2017)).
Tgt Patent Value (citation-weighted)	Target firm's citation weighted (scientific) patent value $\Theta^{cw}_{i,t}$ (obtained from Kogan et al. (2017), and downloaded from their website: https://paper.dropbox.com/doc/U.S.-Patent-Data-1926-2010-t5nuNWnTH1InM0gyxkizL): $$\Theta^{cw}_{i,t} = \sum_{j \in P_{i,t}} \left(1 + \frac{\mathrm{C}_j}{\overline{\mathrm{C}}_j}\right)$$ where $P_{i,t}$ denotes the set of patents issued to the target firm i in year t, C_j is the number of future citations by patent j until the end of the sample period, and $\overline{\mathrm{C}}_j$ is the average number of future citations received by patents granted in the same year as patent j. If the target firm i is issued no patent in year t, the variable $\Theta^{cw}_{i,t}$ is set to 0 (see Kogan et al. (2017)).
Tgt Patent Count (recently granted)	Number of patents the target firm are granted in the whole fiscal year prior to offer announcement. Data come from Kogan et al. (2017), obtained from their website: https://paper.dropbox.com/doc/U.S.-Patent-Data-1926-2010-t5nuN-WnTH1InM0gyxkizL
Tgt Patent Count (total stock)	Total number of patents the target firm are granted until the fiscal year end prior to offer announcement, i.e., yearly counts of United States Patent and Trademark Office (USPTO) patents. Patents must not be expired in order to be included. The data on total stocks are obtained from the University of Virginia (UVA) Darden Global Corporate Patent Dataset (https://patents.darden.virginia.edu/get-data).

Tgt Trade Secrecy Mention Count in 10-K	Number of (wildcard) mentions of either "trade secret", "trade secrets" and/or "trade secrecy" in target firm's most recent 10-K report filed with the SEC prior to offer announcement (*Source: SEC EDGAR 10-K filings*).
Tgt SIC2 Industry R&D Worker Ratio	Ratio of knowledge workers in R&D-related jobs divided by the total number of surveyed participants in a given SIC2 industry-year. R&D-related jobs are defined as all jobs (occupations, denoted "occsoc" in the data, definition online available on: https://usa.ipums.org/usa/volii/acsoccsoc.shtml) coded between 1510XX and 1940YY in the annual American Community Survey (ACS) of the U.S. Census Bureau. The survey size of the ACS is approximately 3.5 million households per year. The ACS data are included in the Integrated Public Use Microdata Series (IPUMS USA, 2020). IPUMS USA collects, preserves and harmonizes U.S. census microdata and provides easy access to this data with enhanced documentation. Data includes decennial censuses from 1790 to 2010, the monthly Current Population Survey (CPS) since 1962, and yearly American Community Surveys (ACS) from 2000 to the present (*Source: https://usa.ipums.org/usa/*). IPUMS does not directly provide industry definitions in the SIC code format. Instead, I manually assign each census code industry definition to the most suitable SIC2 industry and cross-check each industry assignment with the NAICS definition codes, which are available for both datasets. The R&D worker ratios are mapped on a SIC2 industry-year basis to each target firm in the M&A sample on the last fiscal year end date prior to offer announcement.
Tgt Firm Age	Age of the target firm. Measured in years since foundation and obtained at the last fiscal year end date prior to offer announcement (*Source: S&P Capital IQ*).

(Table A1 continued)

Appendix – Table A2

Sample Selection

This table depicts the selection criteria of the final M&A sample with the respective remaining number of observations. After applying filters 1–6, 8,466 observations are left over. The availability of SEC filings, control variables as well as valid data on target firms' past R&D and SG&A spending further restrict the sample to 769 observations.

	Selection criteria	Number of observations
1.	All M&A deals announced between 01/01/2004 and 12/31/2017	475,458
2.	Deal status either "closed" or "withdrawn"	460,243
3.	Acquirer and Target headquartered in the U.S.	98,647
4.	Acquirer and Target publicly listed firms	9,980
5.	Acquirer seeks majority stake and change of control in the Target	8,884
6.	Deal value exceeds USD 1 mm	8,466
7.	Availability of SEC filings and control variables	935
8.	Valid data on Target firm's past R&D and SG&A spending	769

Appendix – Table A3

Modular Regression Setup

Table A3 presents the results of a modular regression setup of linear fixed effects regressions of *BTF Size* on the variable of interest, *Tgt Know Cap Stock*. On a step-by-step basis, I include control variable sets as defined in Section 3. As reported, the regressions (except regression (1)) include *Acquirer Industry* × *Year Fixed Effects* as well as an intercept but are unreported. Regressions (3)–(10) include *Target Industry Fixed Effects*. All standard errors (in parentheses) are adjusted for heteroskedasticity (White (1980)) and within-cluster correlation. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	BTF Size									
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Target Firm Characteristics										
Tgt Know Cap Stock	0.765**	0.765**	0.755**	0.835***	0.834***	0.931***	1.099***	1.051***	1.048***	1.206***
	(0.313)	(0.307)	(0.319)	(0.314)	(0.311)	(0.274)	(0.256)	(0.267)	(0.272)	(0.260)
Tgt Org Cap Stock		0.000	0.035	0.046	0.070	0.098	0.211	0.178	0.237	−0.006
		(0.289)	(0.265)	(0.258)	(0.262)	(0.257)	(0.272)	(0.258)	(0.257)	(0.300)
Tgt Total Intangibles Ratio [OA–22]				2.085**	2.372**	1.798**	1.691**	1.703**		
				(0.896)	(0.912)	(0.803)	(0.798)	(0.794)		
Tgt Goodwill Ratio [OA–22]									2.713*	−0.566
									(1.426)	(2.827)
Tgt Identifiable Intangibles Ratio [OA–22]									0.039	−4.074
									(2.356)	(3.785)
Tgt Tangibility [OA–22]					1.251	0.291	0.327	0.248	0.626	−2.729
					(1.175)	(1.204)	(1.211)	(1.176)	(1.123)	(2.907)
Tgt Current Assets Ratio [OA–22]										−3.719
										(2.608)
Tgt Market-to-Book [OA–22]					0.001	0.013	0.008	0.009	0.032	0.025
					(0.041)	(0.038)	(0.037)	(0.036)	(0.036)	(0.039)
Other Deal Characteristics	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Financial Advisor Fees	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Acquiring Firm Characteristics	No	No	No	No	No	No	No	Yes	Yes	Yes
Acq Industry × Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tgt Industry FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	769	769	769	769	769	769	769	769	729	493
Adjusted R^2	0.012	0.011	0.012	0.021	0.020	0.087	0.088	0.103	0.112	0.122

Appendix – Table A4

Robustness – Heckman Selection Model: Technological Proximity

The table reports fixed effects Heckman (1979) selection models for the selection (i.e., non-randomly selected sample) whether I observe firms' patenting decisions and thus *Technological Proximity*. In the first stage (selection equation), I instrument with both *Tgt SIC2 Industry R&D Worker Ratio* and *Tgt Trade Secrecy Mention Count in 10-K*. Regression sets (1) with (2), and (3) with (4) only differ in the included fixed effects. The Inverse Mills Ratios λ, Wald χ^2-tests of independent equations ($\rho = 0$), and the estimated empirical corrlations of the error terms (1st and 2nd stage) are reported at the bottom of the table. All standard errors (in parentheses) are adjusted for heteroskedasticity (White (1980)) and within-cluster correlation. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Tech Prox non-missing	BTF Size	Tech Prox non-missing	BTF Size
	1st Stage	2nd Stage	1st Stage	2nd Stage
Independent Variables	(1)	(2)	(3)	(4)
Target Firm Characteristics				
Tgt SIC2 Industry R&D Worker Ratio	2.873**		4.135**	
	(1.210)		(1.711)	
Tgt Trade Secrecy Mention Count in 10-K	0.073**		0.080**	
	(0.030)		(0.039)	
Tech Prox Median		−0.101		0.240
		(0.450)		(0.327)
Tgt Know Cap Stock × Tech Prox Median		1.160***		0.969**
		(0.426)		(0.491)
Tgt Know Cap Stock	0.191	0.969***	0.178	0.685*
	(0.123)	(0.305)	(0.137)	(0.397)
Tgt Org Cap Stock	0.128	−0.048	0.092	−0.409
	(0.090)	(0.428)	(0.108)	(0.601)
Inverse Mills Ratio λ		−0.149		−0.162
		(0.378)		(0.451)
Intercept	−1.011	6.079*	−7.013***	2.375
	(1.340)	(3.557)	(1.542)	(2.640)
Other Target Firm Characteristics	Yes	Yes	Yes	Yes
Deal Characteristics	Yes	Yes	Yes	Yes
Acquiring Firm Characteristics	Yes	Yes	Yes	Yes
Acq Industry × Year FE	No	No	Yes	Yes
Tgt Industry FE	Yes	Yes	Yes	Yes
Acq Industry FE	Yes	Yes	No	No
Year FE	Yes	Yes	No	No
Observations (selected; non-selected)	735 (233; 502)		735 (233; 502)	
Pseudo R^2	0.531		0.624	
Adjusted R^2		0.239		0.471
Model p-value	0.000	0.000	0.000	0.000
Wald χ^2-test of indep. eqns. ($\rho = 0$) $\chi^2(1)$		0.160		0.130
{p-value}		{0.685}		{0.716}
Correlation of error terms ρ		−0.059		−0.085
		(0.144)		(0.232)

Appendix – Table A5

Robustness – Variables scaled by Deal Value

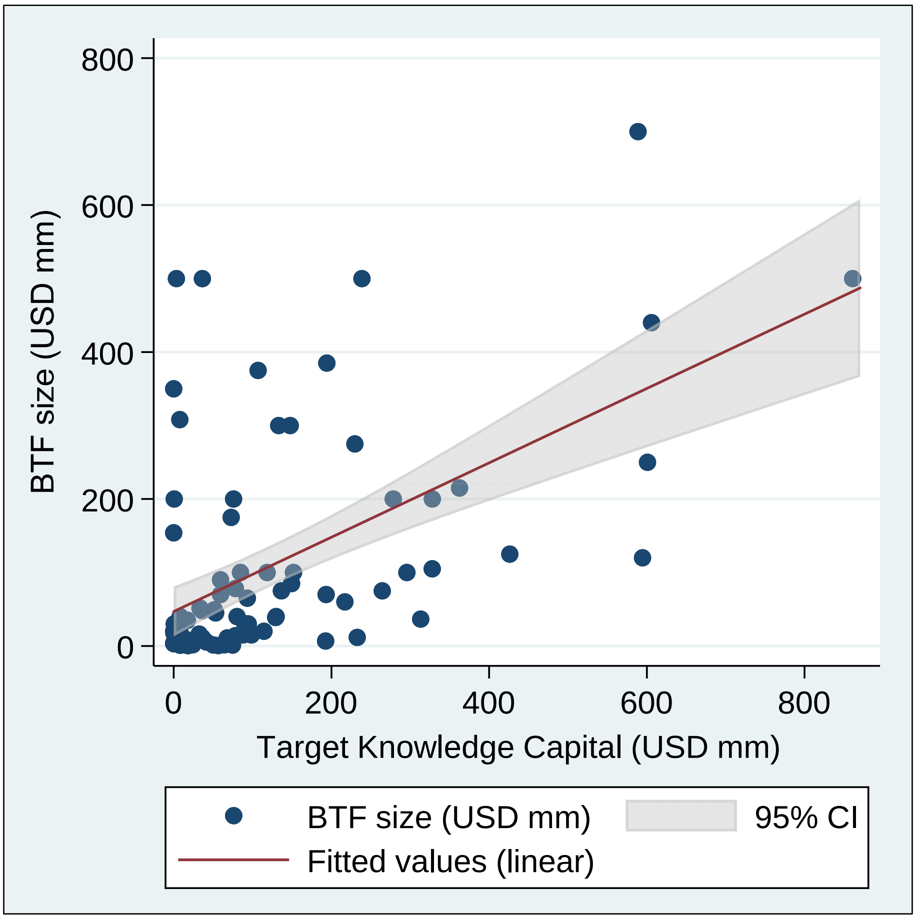
Table A5 presents the results of linear fixed effects regressions of *BTF Size* $_{\textit{Deal Value}}$ on *Tgt Know Cap Stock* $_{\textit{Deal Value}}$ and all control variables used in the baseline regression in Table 2, column (3). The only difference is, that in this table, all key variables (*BTF Size*, *Tgt Know Cap Stock*, *Tgt Org Cap Stock*, *TTF Size*, *Acq All Financial Advisor Fees*, and *Tgt All Financial Advisor Fees*) are scaled by *Deal Value* instead of target firm's market capitalization. Regression (1) includes the same set of other control variables as in Table 2, column (3), and regressions (2)–(4) are modified by including different measures of acquiring firm's financial constraints. All regressions include *Acquirer Industry* × *Year Fixed Effects*, *Target Industry Fixed Effects* as well as an intercept but are unreported. All standard errors (in parentheses) are adjusted for heteroskedasticity (White (1980)) and within-cluster correlation. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	BTF Size $_{\text{Deal Value}}$			
Independent Variables	(1)	(2)	(3)	(4)
Target Firm Characteristics				
Tgt Know Cap Stock $_{\text{Deal Value}}$	0.941**	0.906**	1.163***	1.141***
	(0.403)	(0.385)	(0.350)	(0.363)
Tgt Org Cap Stock $_{\text{Deal Value}}$	0.255	0.218	0.289	0.240
	(0.279)	(0.305)	(0.316)	(0.312)
Tgt Total Intangibles Ratio $_{[\text{OA–22}]}$	1.023*	1.008*	0.880	1.245*
	(0.588)	(0.586)	(0.583)	(0.688)
Tgt Tangibility $_{[\text{OA–22}]}$	0.031	0.365	0.554	0.548
	(0.817)	(0.919)	(0.928)	(0.938)
Tgt Market-to-Book $_{[\text{OA–22}]}$	0.014	0.012	0.023	0.044
	(0.031)	(0.031)	(0.033)	(0.033)
Acquiring Firm Characteristics				
Acq Market Cap $_{[\text{OA–22}]}$	−0.003			
	(0.003)			
ln Acq 1YR Stock Return Volatility $_{[\text{OA–1}]}$	0.248			
	(0.288)			
Acq Market Leverage $_{[\text{OA–22}]}$	0.753			
	(0.857)			
Acq Dividend Payer	−0.641**			
	(0.298)			
Acq Market-to-Book $_{[\text{OA–22}]}$	−0.029**	−0.033***	−0.027*	
	(0.012)	(0.012)	(0.014)	
Acq Hadlock-Pierce-Index		0.621**		
		(0.311)		
Acq Whited-Wu-Index			−0.082	
			(0.071)	
Acq Kaplan-Zingales-Index				−0.000
				(0.003)
Deal Characteristics	Yes	Yes	Yes	Yes
Acq Industry × Year FE	Yes	Yes	Yes	Yes
Tgt Industry FE	Yes	Yes	Yes	Yes
Observations	769	751	697	632
Adjusted R^2	0.104	0.097	0.109	0.102

Appendix – Figure A1

Relation between BTF Size and Target Firm's Knowledge Capital Stock – Bivariate Plot

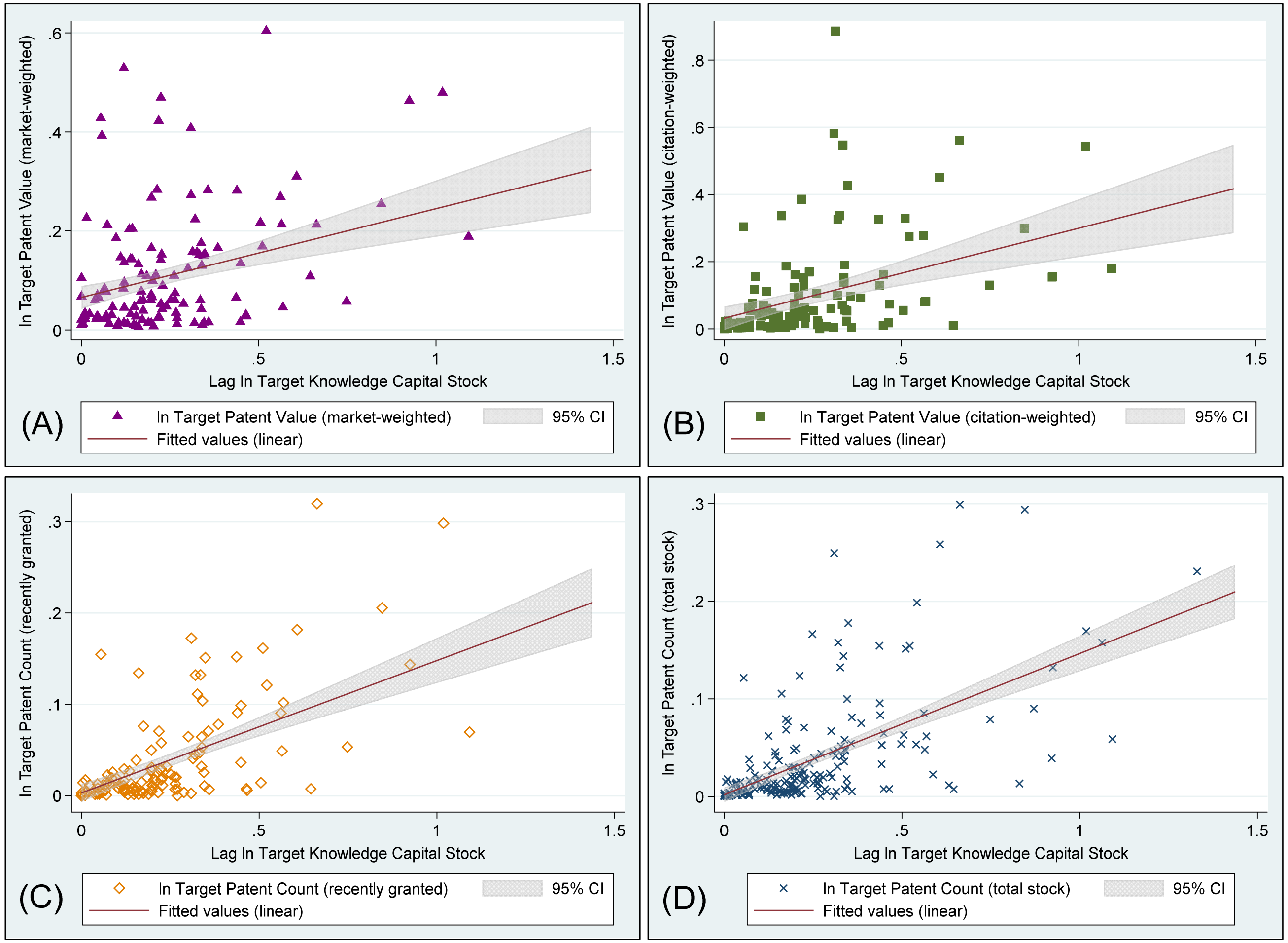
Figure A1 plots *BTF Size* against *Tgt Know Cap Stock*. The data are winsorized at the 1st and 99th percentile.



Appendix – Figure A2

Relation between Target Firm's Patents and Knowledge Capital Stock

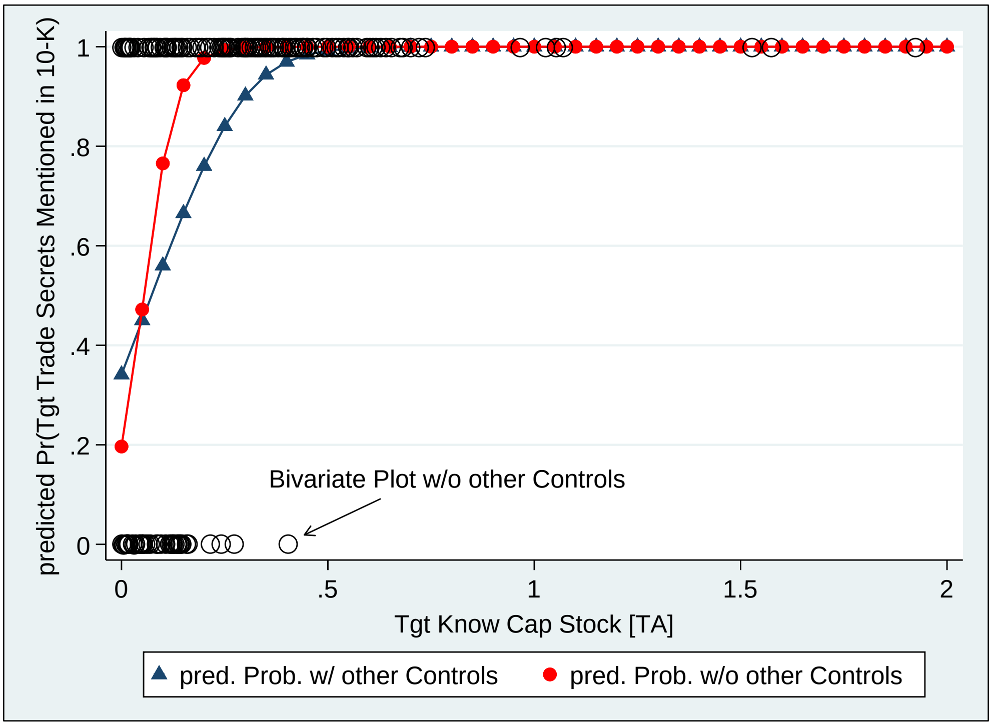
This figure shows the plots of various measures of target firm's patent value (*market-weighted* (A) and *citation-weighted* (B)) and patent count (*recently granted* (C) and *total stock* (D)) to its knowledge capital stock. All four patent measures are obtained at the last fiscal year end date prior to offer announcement. *Target Knowledge Capital Stock* is lagged one year and all variables are scaled by target firm's total assets and are logged. All variables are additionally defined in Table A1.



Appendix – Figure A3

Plot of Predicted Probabilities of Mentioning Trade Secrets in Target Firm's 10-K Report

This figure plots the predicted probabilities of mentioning trade secrets in target's annual 10-K report obtained at the last fiscal year end filing date prior to offer announcement, against target firm's knowledge capital stock scaled by total assets, *Tgt Know Cap Stock* $_{[TA]}$, as defined in the text in Table 10. The hollow black circles represent the simple bivariate plot of realized observations. The blue triangles represent associated predicted probabilities after estimating the fixed effects logit model in Table 10, specification (1), whereas all other independent variables are held at their respective sample mean. The red circles represent associated predicted probabilities after estimating a simple univariate logit model with *Tgt Know Cap Stock* $_{[TA]}$ as the only predictor (i.e., without other controls).



Appendix – Figure A4

Market-to-Book Ratios with and without Intangible Capital Stocks (1975–2017)

Figure A4 depicts the plot of the average (2.5% tail winsorized) market-to-book ratios for all Compustat firms during the 1975-2017 period (289,889 firm-years). The numerator in all series is the sum of market value of equity at the end of the firm's fiscal year, total liabilities and book preferred stock. For the black dot series (A), the denominator is total assets (including acquired intangibles, i.e., "classical"). For the orange dot series (A), the denominator also includes the knowledge and organizational capital stocks ("KC & OC") estimated using the parameters obtained in Ewens et al. (2020). The two dashed, black and orange lines present the simple linear fit of each series. The green dashed line represents the hypothetical market-to-book ratio of 1. In (B), the plot shows the series for firms assigned to the Fama-French 5 industries of both hightech (HT – FF3) and healthcare (HC – FF4). The hollow dots represent market-to-book ratios calculated in the "classical" way (in the same way as the black dots in (A)), and the solid dots are calculated including the knowledge and organizational capital stocks ("KC & OC") in the denominator. The black, orange, and green dashed lines in (B) are copied from (A) for comparison.