Reverse Engineering Innovation When Peers Possess Trade Secrets*

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Abstract

We examine whether reverse engineering activities undertaken by firms are influenced by the extent of trade secrecy in competitor firms. We develop a novel measure for reverse engineering based on abnormal purchasing patterns around firm headquarters, using the Nielsen scanner database. We validate this measure by showing that firms with greater abnormal purchasing behavior near their headquarters are more likely to introduce products and technologies that more closely resemble competitors' offerings, and that competitors experience declines in gross margin when they are subject to higher levels of reverse engineering activity. Using this measure, we find that competitors' use of trade secrecy is associated with increased reverse engineering. The effect is stronger under heightened competition, when hiring competitors' employees is restricted, and varies with the product life cycle. For identification, we leverage the Defend Trade Secrets Act (DTSA). Collectively, our findings highlight reverse engineering as an important but underexplored innovation strategy.

JEL Classifications: L2, M4, O3

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1. Introduction

Reverse engineering, the practice of analyzing and reconstructing competitors' products or technologies, is widely employed by firms seeking to gain competitive insights and accelerate their own innovation efforts (Raja and Fernandes, 2007). While legal in some contexts, reverse engineering is often perceived negatively in the marketplace because it is viewed as appropriating others' innovative ideas, potentially diminishing incentives for future innovation (Samuelson and Scotchmer, 2001). Consequently, firms must decide how to protect their innovations—whether through formal mechanisms like patents, or informal ones like trade secrecy. Despite its importance, surprisingly little is known about reverse engineering activity in general. This study addresses this gap by introducing a novel approach to measuring reverse engineering activity, and asking whether competitors' decision to use trade secrecy (*hereafter* simply trade secrecy) as a protection mechanism shapes the extent of reverse engineering activities undertaken by firms.

The relationship between trade secrecy and reverse engineering activity is not immediately obvious. On the one hand, trade secrecy involves less transparency about the innovation, which can both reduce competitor awareness of the innovation as well as increase the cost and effort required to replicate proprietary technologies, thereby discouraging reverse engineering. On the other hand, trade secrets hold weaker legal protections against imitations compared to patenting innovations, which may embolden competitors to pursue reverse engineering. Moreover, when competitors rely on trade secrecy, firms may view reverse engineering as a necessary substitute for acquiring otherwise inaccessible knowledge. The lack of detailed public information can also signal hidden value, incentivizing firms to invest in uncovering proprietary technologies. As a result, the overall effect of trade secrecy on reverse engineering activities remains theoretically ambiguous, highlighting the need for empirical investigation into this relationship.

A key obstacle in studying reverse engineering is the difficulty of empirically observing such activity directly. To address this, we rely on the insight that reverse engineering typically involves firms purchasing competitors' products to analyze and reconstruct them.[1] Building on this intuition, we use purchasing behavior as an indirect measure of reverse engineering. Specifically, we examine product purchase data from the highly granular Nielsen scanner database to detect unusual buying activity near firm headquarters. By comparing purchasing patterns to the average purchasing activity across other locations, we can identify abnormal spikes in demand that potentially reflect product acquisitions intended for reverse engineering purposes.

To validate the measure, we examine whether abnormal purchasing activity near firm headquarters precedes outcomes consistent with reverse engineering. Reverse engineering is expected to result in increased product imitation and a shift in innovation toward competitors' technologies (Samuelson and Scotchmer, 2001). Using a firm-year panel, we find that such activity precedes the introduction of products and patents that more closely resemble competitors' innovations, and is also associated with higher R&D intensity and patenting. We further find that competitors exposed to greater abnormal purchasing activity experience a decline in gross margins, driven primarily by revenue pressures rather than cost increases. Lastly, abnormal purchasing activity near firm headquarters intensifies in the period leading up to a firm's entry into a new product market, consistent with firms reverse engineering competitors' products in anticipation of entry. Collectively, these patterns validate that our purchasing-based measure meaningfully captures reverse engineering efforts.[2]

[1] See ocpatentlawyer.com – "Reverse engineering is a simple concept: your competitors *purchase your product*, take it apart, and study every element".

[2] In untabulated analysis, we document a positive correlation (0.059) between abnormal product purchasing activity and the number of litigations in which the firm is alleged to have reverse engineered a rival's product (which we use as an alternative proxy for reverse engineering in Section 5.2), strengthening the construct validity of our measure.

Having validated the measure, we examine the relationship between peer firm trade secrecy and reverse engineering. We measure peer firm trade secrecy using the percentage of TNIC competitors that explicitly reference trade secrets in their public filings, following the methodology in Glaeser (2018). Using a sample of 75,963 firm-year observations spanning 2006–2020, our analysis reveals a significant positive relationship between competitors' use of trade secrecy and activities indicative of reverse engineering. Quantitatively, our results indicate that an interquartile increase in competitors' trade secrecy corresponds to a 9.7% increase in reverse engineering activity. This suggests that greater reliance on trade secrecy by competitors increases firm incentives to reconstruct proprietary technologies. In contrast, we observe the opposite pattern when considering patenting activity—reverse engineering is less prevalent when competitors make greater use of patents. Moreover, we do not observe a similar association when we examine abnormal purchases of non-related products, reinforcing that our measure captures targeted strategic behavior rather than general demand or unrelated purchasing activity.

To strengthen our ability to draw causal inference, we exploit the adoption of the Defend Trade Secrets Act (DTSA) as a quasi-exogenous shock that enhanced federal protection for trade secrets. Unlike state-level trade secret laws, the DTSA provides uniform, federal legal protection against misappropriation, reducing the variability inherent in disparate state regimes. Since New York and Massachusetts *did not* adopt the Uniform Trade Secrets Act (UTSA), we consider firms headquartered in these two states as treated. We posit that these firms faced a more pronounced change in trade secrecy protection when the DTSA was enacted. We first demonstrate that affected firms increased their explicit references to trade secrecy by approximately 8.5% after the DTSA took effect, indicating a deliberate strategic shift towards safeguarding proprietary information and validating the shock's influence on trade secrecy. Building on this validation, we find that firms increase reverse engineering activity by 12% for an interquartile increase in the share of TNIC competitors headquartered in the two states treated by the DTSA.

If trade secrecy prompts competitors to pursue reverse engineering more aggressively, this relationship should intensify under heightened competition. Stronger competitive pressures increase the value of gaining insights into rivals' proprietary technologies, as firms face greater urgency to maintain their market positions and technological leadership. We test this prediction by examining tariff reductions, which introduce a relatively exogenous increase in foreign competition (Frésard, 2010). If trade secrecy encourages reverse engineering, we should observe a stronger effect following tariff reductions. Consistent with this reasoning, we find that as competition intensifies due to tariff reductions, the positive relationship between trade secrecy and reverse engineering activity becomes stronger. This result reinforces our primary findings and highlights competition as an important factor influencing firm responses to trade secrecy.

While firms commonly reverse engineer competitor products or technologies to assess rival innovations, another distinct strategy involves hiring employees from rival firms to directly obtain their knowledge and insights. Although hiring competitor employees does not directly imply reverse engineering, it still allows firms to directly learn about rivals' innovations. As such, we examine how limitations on the ability to hire rival employees influence firms' reverse engineering activities by investigating the effects of the Inevitable Disclosure Doctrine (IDD). Since the IDD limits a firm's ability to learn about competitors' trade secrets by restricting employee flows, firms should be more inclined to reverse engineer rival products through direct product purchases. Consistent with this expectation, we find that the positive relationship between trade secrecy and reverse engineering activity is amplified when a higher percentage of peer firms are headquartered in states enforcing the IDD. This result reinforces our primary findings and highlights the substitution effects between hiring rival employees and reverse engineering activities.

Since reverse engineering involves the examination of products and technologies, we next study whether the documented effects depend on the product life cycle stage of (i) the peer firms whose products are targeted by reverse engineering and (ii) the firm engaging in reverse engineering. The incentive to reverse engineer in response to trade secrecy likely depends on the product life cycle of peer firms. Early-stage products embody novel and valuable innovations, making them more attractive targets for reverse engineering. Additionally, early-stage peer firms may lack the financial resources to effectively defend against reverse engineering efforts through legal means. Firms that engage in reverse engineering may also be influenced by the stage of their own product development. Firms in the early stages may be more likely to engage in reverse engineering, as they face strong pressure to develop competitive technologies but often lack extensive internal R&D budgets. Likewise, firms in the declining stage may utilize reverse engineering as a last resort strategy to remain competitive or reposition themselves. Using the 10-K text-based measure of product life cycle stages developed by Hoberg and Maksimovic (2022), we find evidence consistent with these predictions.

We further examine whether our results are robust to using alternative measures of trade secrecy and reverse engineering. First, we verify that our results are robust to restricting TNIC competitors to innovator firms only. Second, rather than relying on firm-level mentions of trade secrecy, we measure trade secrecy using a survey-based approach. Third, we examine a litigation-based proxy by directly counting legal cases in which firms are accused of reverse engineering competitors' products. Finally, we use the abnormal purchasing behavior around firms' R&D labs

(Glaeser et al., 2023) as an alternative measure. Across each of these alternative approaches, we obtain consistent results, which strengthen our main conclusions.

Our study contributes directly to the literature on innovation and disclosure (Roychowdhury et al., 2019; Glaeser and Lang, 2024; Kim and Valentine, 2021, 2023; Dyer et al., 2023; Boot and Vladimirov, 2025) by highlighting an understudied consequence of trade secrecy: competitors' reverse engineering activities. While prior studies primarily focus on the proprietary costs and capital market benefits of patent disclosures (e.g., Glaeser and Landsman, 2019; Kim and Valentine, 2021; Hegde et al., 2023; Oh et al., 2024; Valentine et al., 2025), we provide novel evidence that greater reliance on trade secrecy significantly increases competitors' incentives to uncover and replicate innovations.[3] Our findings provide interesting nuance to the conventional view that trade secrecy limits disclosure-related proprietary costs, suggesting instead that while it may decrease direct access to innovation details, it simultaneously increases the likelihood that competitors reverse engineering such insights indirectly. In this regard, we also make a methodological contribution by introducing a novel approach to measuring reverse engineering by analyzing unusual purchasing behavior near competitors' headquarters. Since reverse engineering is difficult to track directly, this method offers a valuable way to estimate when firms may be analyzing and reconstructing their rivals' products.

Beyond innovation and disclosure, our findings respond to the recent call for more research on trade secrets (Glaeser and Lang, 2024). While secrecy is traditionally viewed as a means for safeguarding proprietary information, our results show that non-disclosure actually encourages reverse engineering efforts. This effect is particularly pronounced in highly competitive environments, where the incentives for imitation are stronger and the costs of secrecy may be

[3] Although not in the context of innovation, Cao et al. (2021) document that mandatory 13F disclosures foster copycat trading strategies by investment companies.

higher. Consequently, our study underscores the need for a more nuanced assessment of innovation disclosure strategies: whether firms should prioritize greater transparency to deter reverse engineering or maintain secrecy at the risk of increased imitation through reverse engineering. By shedding light on these dynamics, our study provides a deeper understanding of the consequences of firm disclosure and the trade-offs between innovation protection and knowledge diffusion.

2. Related Literature and Economic Predictions

2.1 Reverse Engineering

Reverse engineering, the process of analyzing and reconstructing competitors' products or technologies, is commonly employed by firms to gain strategic insights and accelerate their own innovation (Raja and Fernandes, 2007). Reverse engineering plays a significant economic role by fostering competition, spurring follow-on innovation, and is prevalent across various sectors such as manufacturing, semiconductors, and software (Samuelson and Scotchmer, 2001). Survey evidence indicates that reverse engineering is perceived by firms as one of the most effective methods for learning about competitors' products (Levin et al., 1987).

In the U.S., reverse engineering is typically a lawful means of acquiring know-how, especially when conducted through legitimate channels, such as the open market purchase of a product. According to the 1979 Uniform Trade Secrets Act (UTSA) and the 1995 Restatement of Unfair Competition, a trade secret is defined as valuable, secret information that provides a competitive advantage, but it is only protected against discovery by "improper" means. Reverse engineering a product purchased legally is not considered improper, allowing firms to analyze and replicate products they acquire in the marketplace without violating trade secrecy laws.[4]

[4] It is also important to distinguish reverse engineering from the common legal examples of trade secret protection. Unlike the disclosure of trade secrets by employees, a person who buys a product in the open market is not bound by

From an economic standpoint, the legal right to reverse-engineer presents a tradeoff. On one hand, it may reduce incentives for firms to innovate, as it allows competitors to replicate products, potentially leading to wasteful expenditures on reverse engineering. On the other hand, it may foster market competition, drive down prices, and encourage follow-on innovation. Legal frameworks have generally supported reverse engineering, based on the argument that innovators retain protection through two key barriers: the cost and time required for effective reverse engineering (Samuelson and Scotchmer, 2001). These factors allow the original innovator to recoup their R&D investments before competitors can replicate the product.

Samuelson and Scotchmer (2001) outline the four-stage process that firms undergo when engaging in reverse engineering. First, a competitor must be aware that a product is worth reverse engineering. This stage varies in speed across industries, influencing how long the innovator can exclusively profit from its development (Dreyfuss and Kwall, 1996; Curtis et al., 2011).[5] The second stage involves obtaining the product and disassembling and analyzing the product to extract useful technical knowledge. While this process can be costly and time-consuming[6], reverse engineers generally incur lower costs than the original innovator, as they bypass unsuccessful R&D efforts and benefit from technological advancements. Consequently, reverse engineering, as an innovation strategy, has frequently been used by technological laggards to catch-up and learn from first movers and market leaders (Ohly, 2009). The third stage, implementation, requires integrating the extracted knowledge into a marketable product, which can involve extensive

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a contractual duty of confidentiality. Similarly, unlike an industrial spy, the reverse engineering person does not unlawfully enter a competitor's premises. Reverse engineering can only be considered a violation of trade secret law if "breaking into a product" is treated the same as unlawfully entering another company's factory (Ohly, 2009).

[5] Because reverse engineering takes time, both to determine whether a product is worth analyzing and to complete the engineering and market launch, the first mover enjoys a period of exclusivity to recover invention costs, build a reputation, and establish a loyal customer base (Dreyfuss and Kwall, 1996).

[6] Firms may also deliberately design products to make reverse engineering more difficult by using tactics like component encapsulation, mislabeling, custom parts, software locks, or nonfunctional "fingerprints," especially when protecting valuable trade secrets (Samuelson and Scotchmer, 2001; MacAulay and Sharapov, 2025).

prototyping, manufacturing adjustments, and iterative refinements. Lastly, the competitor introduces its version of the product to the market, triggering competitive pressures that may erode the original innovator's market share and profitability.

2.2 Economic Predictions

We posit that the degree to which peer firms use trade secrecy (i.e., the withholding of proprietary information to maintain a competitive advantage) may influence the extent of reverse engineering activities undertaken by firms. On the one hand, greater innovation disclosure, such as through patent filings, can facilitate reverse engineering by reducing the cost and effort required to replicate proprietary technologies (Anton and Yao, 2004). Public disclosures can also increase the visibility of innovations, increasing attention from competitors and prompting imitation and reverse engineering efforts (Kim and Valentine, 2021). On the other hand, reducing disclosure by maintaining greater secrecy may also incentivize reverse engineering activity. When competitors rely on secrecy, they withhold technical details that would otherwise be accessible through formal disclosure. As a result, firms may turn to reverse engineering as a substitute means of acquiring the same knowledge (Matutes et al., 1996; Fromer, 2008). Moreover, firms may interpret competitors' secrecy as a signal of valuable innovations, intensifying reverse engineering. In some cases, firms may pursue reverse engineering not only to imitate, but also to gain insight into a rival's capabilities or anticipate future strategic moves.

The extent to which peer firms' reliance on trade secrecy influences reverse engineering activities is also unclear from a legal perspective. Consider two scenarios of innovation disclosure regimes: in the first scenario, all firms protect their innovations via patents, and in the second scenario, all firms maintain trade secrecy. In the patenting regime, detailed innovation disclosures lower the technical barriers to reverse engineering, making it easier for competitors to replicate innovations. However, because products incorporating patented technologies are protected by enforceable intellectual property rights, firms that reverse engineer such products may face significant litigation risk if they attempt to commercialize the results, potentially offsetting the benefits of reverse engineering. Conversely, under trade secrecy regimes, the absence of public innovation disclosures increases the technical challenges and costs associated with reverse engineering. Yet, since trade secret laws do not prohibit the lawful reverse engineering of products, such as those purchased on the open market, firms may ultimately reap higher benefits once they successfully reverse engineer a rival's innovations, even if the initial costs are higher.

In sum, the overall effect of trade secrecy on reverse engineering activities remains ambiguous, both from an economic and legal perspective, highlighting the importance of empirical investigation into this relationship. Accordingly, we hypothesize in the following null form:

H1: Trade secrecy has no effect on the level of reverse engineering activity by peer firms.

3. Data

3.1 Reverse Engineering

We propose a novel measure of reverse engineering that relies on abnormal product purchasing activity near competitors' headquarters. While indirect, this method allows us to infer the level of reverse engineering activity at the firm-quarter level for several reasons.

First, reverse engineering typically requires firms to acquire multiple units of a competitor's product for destructive testing, teardown analysis, firmware extraction, and benchmarking. Firms often purchase additional units to support testing under different environmental or usage conditions (e.g., temperature, voltage, wear) or to validate results across multiple iterations.[7] Second, reverse engineering activities often involve multiple functional teams within a firm, including R&D, engineering, manufacturing, and quality assurance. Each team may require independent access to the product for analysis aligned with its function (e.g., materials breakdown by engineering, user interface analysis by design, packaging study by marketing). Especially in large, decentralized firms, this coordination requires the purchase of multiple units.[8] Lastly, abnormal purchasing is likely to spike near a firm's headquarters because reverse engineering efforts are concentrated where technical decision-making occurs. As Glaeser et al. (2023) show, the most valuable innovation activities are disproportionately located near headquarters.[9] This geographic concentration means that purchasing activity around firm headquarters is more likely to reflect reverse engineering, rather than local consumer demand.

We gather scanner datasets from Nielsen Retail Measurement Services (RMS), made available through the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business. This dataset is derived from point-of-sale (PoS) systems in grocery, drug, and general merchandise stores and spans more than 40,000 stores across the entire U.S. retail market at the weekly level over the period 2006–2020. Each store reports weekly quantities purchased for every product with recorded transactions during that period. These scanner datasets provide high-

[7] For instance, anecdotal evidence suggests that reverse engineering consumer products, such as cosmetics, involves systematic lab testing, ingredient deconstruction, and iterative formulation replication. These processes typically require the acquisition of multiple product units to ensure consistency across sensory attributes, chemical composition, and product stability.

[8] An example is General Motors' teardown of the Lexus RX 400h hybrid SUV. At its Warren Technical Center, located near headquarters, GM disassembled multiple units to analyze materials, design, and cost. Separate teams handled teardown, structural analysis, and cost benchmarking, highlighting how reverse engineering involves multiple units and cross-functional coordination across engineering, design, and procurement divisions. Consistent with this, we find that firms with more diverse R&D operations, proxied by the number of unique R&D-related job titles (e.g., "Mechanical Engineer," "Materials Scientist," "Product Designer"), exhibit a positive association with our reverse engineering measure (untabulated).

[9] In Section 5.2, we demonstrate that our inferences are robust to using companies' R&D labs as an alternative location for product purchases.

frequency purchasing behavior for more than one million unique products (i.e., Universal Product Codes [UPCs]), which are categorized into 1,070 detailed product modules.[10]

To construct a firm-quarter measure of reverse engineering, we begin with the set of Compustat firms with TNIC competitors reported in the Neilsen scanner dataset.[11] This identifies 6,334 firms with at least one competitor reporting sales in the Neilsen data. For each competitor firm, we determine the product modules they sell, creating a firm-to-product mapping that highlights potential products acquired for reverse engineering purposes. By focusing on product modules, we can capture both TNIC competitors' products and products offered by private firms. This broader scope provides a more comprehensive view of reverse engineering activity and improves the generalizability of our findings (Armstrong et al., 2022).

For each firm, we aggregate the total purchase volume of competitor product modules every quarter that come from the firm's headquarter zip code (available at the 3-digit level). To account for baseline purchasing patterns across different locations, we scale the total product purchases in a geographic region by their respective population to control for potential regional variations in demand. Then, we adjust the total volume of purchases by subtracting the average volume of purchases (also scaled by their respective populations) in all zip codes during the same quarter. This adjustment normalizes the measure, ensuring that it reflects an excess concentration of purchases relative to general market trends rather than simply capturing regional demand differences. Figure 1 presents an illustration of our methodology using an example.

We define *Reverse Engineering* for firm *i* headquartered in zip code *j* in quarter *t* as follows:

[10] Nielsen-defined product modules serve as the first level of aggregation beyond individual UPC barcodes, capturing detailed product characteristics. For instance, within the pharmaceuticals category, distinct modules may include items like "over-the-counter pain relievers," "allergy medications," and "digestive health products," providing a granular classification of product markets served by firms.

[11] For matching UPCs to public firms, we follow Zeng (2024) and use data from GS1 US, which maintains a comprehensive record of company prefixes issued in the U.S. We initially identify 889 public firms, 515 of which have corresponding TNIC data.

$$Reverse\ Engineering_{i,t} = \frac{P_{i,j,t}}{Population_{j,t}} - \overline{\left(\frac{P_{i,k,t}}{Population_{k,t}}\right)}_{k \neq j} \tag{1}$$

where $P_{i,j,t}$ refers to the total volume of purchases of products that are competitors to firm i in zip code j during quarter t and $\overline{\left(\frac{P_{i,k,t}}{Population_{k,t}}\right)}_{k \neq j}$ refers to the average per-capita volume of purchases of competitor products to firm i in all non j zip codes during quarter t. Accordingly, the measure captures the degree to which competitor products are disproportionately purchased near a firm's headquarters, potentially reflecting product acquisitions intended for reverse engineering purposes.[12]

Table 1 presents the sample selection procedure in more detail. From the identified 6,334 unique firms, we remove 1,346 firms without headquarter zip code data required to construct our geography-based measure of reverse engineering. We further remove 735 financial firms (i.e., firms classified in the 4-digit SIC industries: 6000-6999). Lastly, we remove 685 firms without data on firm-level control variables (constructed from Compustat and USPTO datasets). This procedure leaves us with 3,568 firms, with which we construct a panel of 75,963 firm-year observations for our main analyses.

3.2 Research Design

To examine the relationship between peers' trade secrecy and reverse engineering, we estimate the following OLS regression:

$$Reverse\ Engineering_{i,t} = \alpha + \beta\ Peer\ Trade\ Secrecy_{i,t-1} + X_{i,t-1} + \gamma_i + \nu_t + \varepsilon_{i,t} \tag{2}$$

where i and t refer to firm and quarter, respectively. The dependent variable is *Reverse Engineering* measured for firm i in quarter t. The primary explanatory variable of interest is *Peer Trade Secrecy*,

[12] For empirical analyses, we take the inverse hyperbolic sine transformation of the variable since the raw abnormal variable can take nonpositive values (Burbidge et al., 1988).

which is defined as the percentage of TNIC competitors of firm *i* that explicitly reference trade secrecy in their public filings (Glaeser, 2018).

We include a host of firm-level control variables (*X*) to better isolate the effect of peers' trade secrecy on reverse engineering. We categorize these control variables into four groups. First, we account for general firm characteristics, including (i) firm size (*Size*), (ii) return on assets (*ROA*), and (iii) firm age (*Firm Age*). Second, we control for innovation variables by including (iv) R&D intensity (*R&D/Assets*), (v) number of patents filed (*Log(1+#Patents Filed)*), (vi) average patent economic value (*Avg Patent Value*), and (vii) selling, general, and administrative expenses (*SG&A/Sales*). Third, we include financial leverage (*Leverage*) to control for the firm's financial constraints. Lastly, we control for the industry-level competition by including Herfindahl-Hirschman Index (*HHI*).[13] All independent variables are lagged by one quarter. In our most stringent specification, we include both firm (γ) and quarter (v) fixed effects to control for time-invariant firm characteristics and broader time trends, respectively. We cluster standard errors at the industry-year level. If heightened trade secrecy among peer firms incentivizes focal firms to engage in more (less) reverse engineering, we expect β to be positive (negative).

3.3 Descriptive Statistics

Table 2 presents the descriptive statistics of our sample. Panel A presents the summary statistics of the variables used in our main analyses. The mean value of *Reverse Engineering* is 0.038, with a standard deviation of 0.083, suggesting substantial variation across firms. *Peer Trade Secrecy*, our primary explanatory variable, has a mean of 0.681, indicating that, on average, 68.1% of TNIC competitors explicitly reference trade secrecy in their public filings. The average firm in our sample has 573 million in total assets (*Firm Size* = 6.352; $e^{6.352}$ = 573 million). The average

[13] Variable descriptions are provided in Appendix A.

firm's R&D expenses take up 2.4% of total assets (*R&D Intensity* = 0.024), whereas the median firm exhibits an *ROA* of 0.6%.

Panel B of Table 2 presents the industry distribution of firms, showing the most common industries based on 4-digit SIC industries, along with their corresponding mean and median values of *Reverse Engineering*. Firms in the Pharmaceutical Preparations (SIC 2834) industry take up the largest proportion of our sample (6.21%). Our sample includes a substantial number of firms from other innovation-driven sectors, such as Biological Products (SIC 2836) and Prepackaged Software (SIC 7372) industries, which each take up 4.5% and 4.27% of the sample, respectively. We document significant variation in *Reverse Engineering* across industries. Semiconductors (SIC 3674) and Electronic Components (SIC 3670) exhibit relatively high levels of reverse engineering (median = 0.076 and 0.074, respectively), consistent with the notion that these industries are characterized by rapid technological change and increased incentives to analyze competitors' products. Similarly, Eating Places (SIC 5812) exhibits high levels of reverse engineering (median = 0.085), reflecting competitive pressures in the restaurant industry where firms frequently replicate successful product offerings.[14] In contrast, Computer Programming Services (SIC 7371) and Business Services (SIC 7389) industries have relatively lower levels of reverse engineering.

4. Empirical Results

4.1 Validation of Measure

To strengthen confidence in our measure for reverse engineering activity, we conduct a series of validation tests. While our measure captures abnormal product purchasing activity near a firm's headquarters, it does not directly reveal whether these purchasing spikes correspond to

[14] Anecdotal evidence suggests that many food scientists are tasked with replicating the taste, texture, and composition of existing products. For example, the popular Oreo cookie was itself a reverse-engineered version of Hydrox, an earlier cream-filled chocolate cookie (see snipettemag.com).

reverse engineering activities. Thus, we evaluate whether abnormal product purchasing behavior around firm headquarters precedes outcomes that would be expected if the purchases reflect reverse engineering activity (Samuelson and Scotchmer, 2001). We conduct three validation tests.

First, we examine whether firms with higher abnormal product purchasing behavior are more likely to subsequently produce offerings that are more similar to competitors' products, and file patents in overlapping technological domains. Reverse engineering provides firms with detailed technical insight into the design, materials, and functionality of competitors' products. Such insight can accelerate the development of related technologies, ultimately leading firms to file patents in areas that closely resemble their competitors' innovations.[15] Second, we examine whether reverse engineering imposes competitive pressure on peers, as reflected in a decline in peer firms' gross margins. Third, we examine whether abnormal product purchasing around corporate headquarters intensifies in the period leading up to a firm's entry into a new product market. If abnormal product purchasing is indeed capturing reverse engineering activity, we should observe an uptick in such activity in the period preceding the firm's announcement of its entry into a new product market.

For the first two tests, we estimate the following regression model at the firm-year level:

$$Y_{i,t+1} = \alpha + \beta \mathit{Reverse\ Engineering}_{i,t} + X_{i,t} + \gamma_i + \nu_t + \varepsilon_{i,t} \qquad (3)$$

where *i* and *t* refer to firm and year, respectively. The dependent variable (*Y*) is one of the four variables measured for the focal firm *i* at year *t+1*: *Product Similarity*, *Tech Similarity,* or *Peer Gross Margin*. *Product Similarity* is the equal-weighted average product similarity score between

[15] If a firm successfully reverse engineers a competitor's product—typically protected by a combination of patents and trade secrets—it generally cannot patent the already disclosed elements and may face litigation risk if it commercializes them. However, the insights gained from reverse engineering can guide related, patentable innovations, help the firm innovate around existing patents, or even leapfrog competitors by developing more advanced technologies.

the focal firm and its TNIC competitors (Hoberg and Phillips, 2010; 2016). *Tech Similarity* is the share of patent portfolios in the same technological classes between the focal firm and its TNIC competitors (Jaffe and Trajtenberg, 1996). *Peer Gross Margin* is the median gross margin of the focal firm's TNIC competitors.[16] The primary explanatory variable of interest is the decile-ranked *Reverse Engineering* measured for firm i at year t. We decile-rank the variable to aid interpretation of the regression results. We include the same set of firm-level control variables (X) as in Eq. (2), as well as firm (γ) and year (ν) fixed effects.

Table 3 Panel A presents the results. In column 1, we find a positive and statistically significant (1% level) coefficient on *Reverse Engineering* (coeff. = 0.0035; t = 2.97) and product similarity. In terms of economic significance, moving from the bottom to top decile of *Reverse Engineering* is associated with a 4.8% (= 0.0035 ÷ 0.072) increase in product similarity in the following year. In column 2, we find a positive and statistically significant (10% level) coefficient on *Reverse Engineering* (coeff. = 0.0267; t = 1.82) and technological similarity. In terms of economic significance, moving from the bottom to top decile of *Reverse Engineering* is associated with a 5.1% (= 0.0267 ÷ 0.520) increase in technological similarity in the following year. Moreover, if firms are using product purchases to reverse engineer competitor offerings, this should be reflected in subsequent increases in innovation activity. Consistent with this interpretation, we observe a positive and statistically significant association between *Reverse Engineering* and R&D intensity (column 3; coeff. = 0.0104; t = 3.03) and the number of patents filed (column 4; coeff. = 0.0562; t = 1.78) in the following year.

Table 3 Panel B presents the results for profitability. In column 1, we find a negative and statistically significant (1% level) relation between *Reverse Engineering* and peers' gross margins

[16] We use the median value, since gross margins are highly skewed. Our inferences are the same when we use the mean value (untabulated).

(coeff. = -0.0313; t = 3.48). In terms of economic significance, moving from the bottom to top decile of *Reverse Engineering* leads to an 8.7% (= -0.0313 ÷ 0.072) decrease in peers' gross margins in the following year. We further examine whether the decrease in gross margins is driven by changes in sales growth (*Peer % Sales Growth*) or cost structure (*Peer % COGS Growth*). If peer firms face increased competition due to reverse engineering, the decrease in gross margins will be driven by a reduction in sales rather than an increase in costs, as peers may be forced to lower prices or lose market share. In column 2, we find a negative and statistically significant (10% level) coefficient on *Reverse Engineering* (coeff. = -0.0133). However, in column 3, we find a statistically insignificant coefficient on *Reverse Engineering*. Thus, the results suggest that the decline in gross margins is more likely driven by revenue pressures rather than cost increases.

Collectively, these results strengthen the construct validity of our measure. Firms with higher abnormal product purchasing activity are more likely to launch products that resemble competitors' offerings and file patents in overlapping technological areas. Their activities also coincide with a decline in peers' profitability, consistent with competitive pressures from reverse engineering activities.[17] These patterns strongly suggest that abnormal product purchasing behavior captures (on average) successful reverse engineering activity.[18]

We next examine whether abnormal product purchasing around corporate headquarters intensifies in the period leading up to a firm's entry into a new product market. To test this idea, we identify firms that enter new product markets during our sample period using the product market scope data developed by Hoberg and Phillips (2025). This data provides firm-year

[17] We also find that these peers are more likely to include language in the risk factor section of their 10-K filings warning that competitors may copy or reverse engineer their products or technology (untabulated).

[18] Note that not all reverse engineering efforts are successful. Abnormal product purchases around headquarters serve as a proxy for a firm's *attempt* to reverse engineer, but whether these attempts succeed will necessarily depend on the firm's ability to extract, replicate, and integrate the acquired knowledge. If reverse engineering efforts fail, whether due to technological complexity or lack of internal capabilities (e.g., Curtis et al., 2011), we should not empirically observe these patterns. Therefore, our analyses reveal that, on average, firms are successful in reverse engineering.

measures of product market activity by mapping firm business descriptions into a 300-dimensional representation of the U.S. product market space. A firm is classified as entering a new product market if it begins operating in one of these 300 markets in a year where it had no prior presence. To link market entry to the types of products firms are likely to reverse engineer, we map the representative keywords for each product market (as defined by Hoberg and Phillips, 2025) to product module descriptions in the Nielsen Retail Scanner data.[19] This mapping allows us to identify the product categories firms may plausibly purchase in anticipation of market entry. We then use product release announcements from RavenPack News Analytics to pinpoint the timing of entry events.[20] This process yields 115 entry events across 99 unique firms.

For each event, we construct a balanced 96-month event-time panel (i.e., 48 months before and after the market entry) centered on the product release announcement month. We measure abnormal product purchases in the firm's headquarters zip code using the methodology described earlier and compute the average across all events. Figure 2 presents the event-time analysis. We compare two groups: (i) treated firms that announce entry into a new product market and (ii) control firms from the same TNIC industry, headquartered in a *different* zip code, that do *not* enter the product market at any point during the sample period. We observe a clear divergence in abnormal product purchases between treated and control firms in the months leading up to market entry. Firms that enter a new product market exhibit higher levels of abnormal product purchasing relative to control firms as early as 48 months prior to the product announcement, whereas the gap narrows substantially following market entry.[21] These patterns are suggestive of firms reverse

[19] We retain only direct matches where at least one representative keyword from the product market appears exactly within the product module name.

[20] We classify a firm's product release announcement as corresponding to a specific product market using the textual similarity between the news headline and the keywords associated with each of the 300 product markets.

[21] This pattern is consistent with prior evidence suggesting that it typically takes one to three years to replicate competitors' innovation (Levin et al., 1987).

engineering products in anticipation of market entry. Further, the absence of a similar trend among control firms helps mitigate concerns that abnormal product purchasing around firm headquarters reflects broader economic conditions or industry-wide shocks.

4.2 Main Results

We examine the relation between trade secrecy and reverse engineering by estimating Eq. (2). Table 4 Panel A presents the results. In column 1, we present results for the baseline specification without firm or quarter fixed effects. The coefficient on *Peer Trade Secrecy* is 0.0065 and statistically significant at the 5% level (t = 2.36), suggesting a positive association between trade secrecy and reverse engineering. In column 2, we introduce firm and quarter fixed effects and continue to document a positive and statistically significant (1% level) coefficient on *Peer Trade Secrecy* (coeff. = 0.0057; t = 2.83). In column 3, we further include firm-level control variables and continue to find that the coefficient for *Peer Trade Secrecy* remains positive (0.0060) and statistically significant at the 1% level (t = 2.93). Focusing on column 3, in terms of economic magnitude, an interquartile increase in *Peer Trade Secrecy* is associated with a 9.7% (= (0.967-0.350) × 0.006 ÷ 0.038) increase in reverse engineering activities, relative to the sample mean. Overall, our findings support the hypothesis that firms engage in more reverse engineering when competitors rely on trade secrets.

In terms of control variables, we also find that *Leverage* is positively associated with reverse engineering (t = 3.20), suggesting that more financially constrained firms have stronger incentives to reverse engineer competitors' products. These firms may have stronger urgency to generate cash flows and stay solvent, which incentivize them to supplement formal innovation channels with reverse engineering. In contrast, *HHI* is negatively associated with reverse engineering (t = -3.43), indicating that firms in more concentrated industries engage in less reverse engineering, possibly due to higher barriers to entry or reduced competitive pressures.

We further examine the relation between competitors' patenting activities and reverse engineering. Table 4 Panel B presents the results. In column 1, we find a negative and statistically significant association between the average number of patents filed by peer firms (*Peer Log(1+#Patents Filed)*) and reverse engineering (coeff. = -0.0117; t = -7.55). In column 2, we use the average value of patents filed by peer firms (*Peer Avg Patent Value*) and similarly document a significant negative relation (coeff. = -0.1824; t = -5.81). In terms of economic magnitude, an interquartile increase in *Peer Log(1+#Patents Filed)* (*Peer Avg Patent Value*) is associated with a 23% (19%) decrease in reverse engineering, relative to the sample mean. These results suggest that when competitors rely more heavily on patents (or have more valuable patents), reverse engineering activity is curtailed. Patents publicly disclose detailed specifications and legal boundaries, which may either deter reverse engineering attempts due to litigation risk or reduce the need for reverse engineering by providing access to technological knowledge directly.

However, the extent to which patents deter reverse engineering may depend on how clearly they disclose technical information. To explore this possibility, we examine the vagueness of peer firms' patent filings (Arinas, 2012). While patents are meant to disseminate knowledge in exchange for legal protection, claims may be strategically drafted using broad or ambiguous language to obscure key details. We expect industries with more vague patents to exhibit greater reliance on reverse engineering, as firms may need to analyze physical products to understand competitors' innovations. We measure *Peer Vague Patents* as the percentage of patents by peer firms that contains vague language.[22] In column 3 of Table 4 Panel B, we find a positive and statistically significant association between *Peer Vague Patents* and reverse engineering (coeff. = 0.1831; t = 3.54), consistent with the idea that obfuscation in peers' patent filings incentivizes competitors toward reverse engineering as an alternative information-gathering strategy.

4.3 Defend Trade Secrets Act (DTSA) as a Shock to Trade Secrecy

Identifying the causal effect of competitors' trade secrecy on reverse engineering is challenging in a panel regression setting due to potential endogeneity concerns. First, competitors' reliance on trade secrecy is likely not random and may be influenced by the nature of innovation and the risk of reverse engineering (Moser, 2012). This introduces the reflection problem, making it difficult to disentangle the direction of causality (e.g., Manski, 1993). Second, unobserved firm characteristics could drive both trade secrecy adoption and reverse engineering. While including firm fixed effects in Eq. (2) helps mitigate such time-invariant unobserved heterogeneity, these fixed effects do not address time-varying shocks that may simultaneously affect peers' reliance on trade secrecy and the focal firm's reverse engineering.

To address these challenges, we exploit the Defend Trade Secrets Act (DTSA) of 2016 as a quasi-exogenous shock to trade secrecy, allowing us to establish a more credible causal link between trade secrecy and reverse engineering (Sran, 2025; Cunningham and Kapacinskaite, 2025). The DTSA provides stronger federal legal protections for trade secrets, particularly affecting firms in states that had not previously adopted the UTSA.[23] In particular, at the time of

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[22] See Appendix A for the list of keywords or phrases that indicate vagueness in patent filing descriptions. Patents are matched to industries following Kim and Valentine (2023) using the crosswalk file developed by Goldschlag et al. (2016). We exclude firm-years with no patents matched to any industries for this analysis.

[23] It is important to note that the DTSA does not prohibit reverse engineering from legally acquired products in the open market, as this remains a lawful means of obtaining know-how (see our discussion in Section 2.1). Therefore, while the DTSA strengthens trade secret protection against unlawful misappropriation, it does not extend to restricting competitive practices like reverse engineering that we capture via our scanner dataset. As such, our analysis treats the DTSA as a general shock prompting affected firms to shift toward trade secrecy, but we do not interpret this shift as due to an increase in protection from reverse engineering based on open-market purchases.

DTSA passage in 2016, two states (New York and Massachusetts) have not adopted UTSA. Thus, for treated firms, we consider firms headquartered in NY or MA and posit that these firms are more likely to rely on trade secrecy following the enactment of DTSA. We implement a difference-in-differences (DiD) design to compare firms in affected and unaffected states over a four-year period, excluding the year of adoption (2016), with two years before and after its passage.

We first validate the shock's premise by examining whether these firms make more explicit references to trade secrecy in their public filings following the passage of DTSA. Specifically, we estimate the following DiD specification using a Poisson regression at the firm-year level[24]:

$$\# \, Trade\ Secrecy\ Words_{i,t} = \alpha + \beta Post\ DTSA_t \times Affected\ States_i + X_{i,t} + \gamma_i + \nu_t + \varepsilon_{i,t} \quad (4)$$

where *i* and *t* index firm and year, respectively. The dependent variable is *# Trade Secrecy Words*, defined as the number of trade secrecy-related words in firm *i*'s public 10-K filing in year *t* (Glaeser, 2018). The primary explanatory variable of interest is the interaction term (*Post DTSA* × *Affected States*). *Post DTSA* is an indicator variable that equals one (zero) for observations that fall in 2017 or 2018 (2014 or 2015). *Affected States* is an indicator variable that equals one for firms headquartered in the state of NY or MA, else zero.[25] *X* refers to the same set of firm-level control variables included in Eq. (2). We include firm (γ) and year (ν) fixed effects. If DTSA passage increases affected firms' propensity for trade secrecy, we expect β to be positive.

Table 5 Panel A presents results of Eq. (4). In column 1, we present the findings without control variables to mitigate the "bad controls" problem in a DiD specification (e.g., Angrist and Pischke, 2009; Gormley and Matsa, 2016). In column 2, we estimate the DiD specification with the inclusion of firm-level control variables. In both columns, we document a positive and

[24] We employ a firm-year panel as the dependent variable (*# Trade Secrecy Words*) is measured at the firm-year level. We also conduct a Poisson regression since the dependent variable is a count variable (Cohn et al., 2022).
[25] To fix the set of treated firms over the span of the DiD window, we exclude TNIC competitors that changed their headquarters to or from NY or MA during the DiD period.

statistically significant coefficient on *Post DTSA* × *Affected States*, indicating that affected firms did shift towards trade secrecy following the enactment of DTSA. Regarding economic magnitude, affected firms increase references to trade secrecy by approximately 8.5% (=$e^{0.0815}$ – 1) after the DTSA (column 2). We further conduct a pre-trends analysis by replacing *Post DTSA* with indicator variables for each year pre-DTSA and two years post-DTSA (with year 2015 omitted and used as the benchmark). Figure 3 Panel A shows no evidence of pre-trends: the coefficients on the interaction terms become statistically significant in the two years following the DTSA passage.

Having established that DTSA passage increases affected firms' propensity to rely on trade secrecy, we next turn to our main test of examining whether peer firms' trade secrecy (via DTSA passage) affects focal firm's reverse engineering activities. We create a continuous treatment variable *(% Affected Peers*) that captures the percentage of TNIC competitors headquartered in the state of NY or MA.[26] We then estimate an analogous DiD specification to Eq. (4) but at the firm-quarter level employing an OLS regression (with 2016Q2, the quarter of DTSA passage, omitted):

$$\textit{Reverse Engineering}_{i,t} = \alpha + \beta \textit{Post DTSA}_t \times \textit{\% Affected Peers}_i + X_{i,t} + \gamma_i + \nu_t + \varepsilon_{i,t} \qquad (5)$$

where *i* and *t* index firm and quarter, respectively. The dependent variable is *Reverse Engineering* measured for firm *i* in quarter *t*. We include firm-level control variables (*X*) as in Eq. (2) along with firm (γ) and quarter (ν) fixed effects.[27]

Table 5 Panel B presents the results of Eq. (5). Our findings show that after DTSA enactment, firms with a large share of peers headquartered in NY or MA (i.e., affected states) saw an increase in reverse engineering activity. In both columns, the interaction term coefficient is

[26] We acknowledge that, in principle, all firms could be treated under the DTSA due to the ability to stack federal and state-level claims. To address this concern, we conduct an untabulated robustness check using a continuous treatment variable, which captures cross-state variation in the strength of UTSA prior to the DTSA's passage (Png, 2017). Our inferences remain robust.
[27] *Post DTSA* and *Affected States* are absorbed by quarter and firm fixed effects, respectively.

statistically significant at the 1% level. Further, the results are economically significant: firms' reverse engineering activities increase by 12% for an interquartile increase in *% Affected Peers* after the DTSA passage (= (0.225-0.031) × 0.0234 ÷ 0.038). Further, Figure 3 Panel B presents no evidence of pre-trends surrounding the DTSA passage. Overall, the DiD findings corroborate the panel regression results and support the notion that heightened trade secrecy leads competitors to intensify their reverse engineering efforts.

4.4 Cross-sectional Variations

4.4.1 Product Market Competition

We posit that the trade secrecy-reverse engineering relation will exhibit cross-sectional variation depending on the level of competitive pressure faced by firms. Firms in highly competitive industries face stronger incentives to quickly replicate rivals' innovations to maintain market position, and such incentives will be especially magnified when peers are maintaining greater secrecy regarding their innovations (Vives, 2008; Spulber, 2013). To examine this conjecture, we use tariff reductions as a relatively exogenous proxy for increased product market competition (Frésard, 2010). Tariff reductions are known to expose firms to an increase in foreign competition.[28] We define significant tariff reductions as instances where the industry-level tariff falls by more than three times the median tariff decrease and is neither preceded nor followed by a tariff increase of comparable magnitude (*I (Signif. Tariff Reduction)* = 1).

To explore this prediction, we extend Eq. (2) by introducing *I (Signif. Tariff Reduction)*, an indicator variable that equals one if the firm's industry experienced a significant tariff reduction in the previous year, else zero. We then interact this indicator with *Peer Trade Secrecy*. The results are tabulated in Table 6. We find a positive and statistically significant coefficient on the

[28] It is well established that tariff reductions are shocks that increase product market competition for domestic firms (e.g., Valta, 2012; Huang et al., 2017; Bernard et al., 2020; Glaeser and Landsman, 2021; Afrin et al., 2024).

interaction term, *Peer Trade Secrecy × I (Signif. Tariff Reduction)*, at the 10% level (coeff. = 0.0084), which indicates that the relationship between trade secrecy and reverse engineering is strengthened following a significant tariff reduction. These results are consistent with competitive forces reinforcing firms' incentives to reverse engineer in the presence of peer trade secrets.

4.4.2 Talent-Based Knowledge Acquisition

Reverse engineering is a widespread tactic for assessing competitors' innovations, but hiring employees from rival firms offers another route to similar proprietary knowledge. While this approach doesn't constitute reverse engineering, it enables firms to tap directly into the expertise of their rivals. As such, we examine how limitations on the ability to hire rival employees influence firms' reverse engineering activities by investigating the effects of the Inevitable Disclosure Doctrine (IDD) (Klasa et al., 2018). We anticipate that the relationship between trade secrecy and reverse engineering is more pronounced when a larger share of peer firms is headquartered in states enforcing the IDD (*High % of IDD Peers* = 1). By increasing the cost of acquiring proprietary knowledge through labor mobility, IDD enforcement may push firms to rely more heavily on reverse engineering through product purchases.

To explore this prediction, we extend Eq. (2) by introducing *High % of IDD Peers*, an indicator variable that equals one if the percentage of TNIC competitors headquartered in states that enforce the IDD is above the sample median, else zero. We then interact this indicator with *Peer Trade Secrecy*. In Table 7, we find a positive and statistically significant coefficient on the interaction term, *Peer Trade Secrecy × High % of IDD Peers*, at the 5% level (coeff. = 0.0050), indicating that the relationship between competitor trade secrecy and reverse engineering is more pronounced when firms face greater restrictions on hiring rival employees.

4.4.3 Product Life Cycle Stage

Since reverse engineering involves the examination of products and technologies, we next examine whether the effects documented depend on the product life cycle stage of (i) the rival firms whose products are being targeted by reverse engineering and (2) the firm engaging in reverse engineering (Klepper, 1996). To explore these cross-sections, we employ the 10-K text-based measure of product life cycle used by Hoberg and Maksimovic (2022) and Chen et al. (2023). Hoberg and Maksimovic (2022) propose a four-stage product life cycle that consists of the following stages: (i) product innovation (*Life1*), (ii) process innovation (*Life2*), (iii) product maturity (*Life3*), and (iv) product decline/discontinuation (*Life4*) and measure a firm's exposure to each of these stages using the discussions in 10-K filings.[29]

First, we categorize peer firms (i.e., firms targeted by reverse engineering) into one of the four product life cycle stages (*pLife1* to *pLife4*). We identify the TNIC competitors of each focal firm. For each competitor grouping, we take the average of their *Life1* to *Life4* loadings, denoted as *pLife1*, *pLife2*, *pLife3*, and *pLife4*. Next, we determine the maximum value among *pLife1* to *pLife4*. The competitor group is then assigned to one of the four life cycle stages based on the average with the maximum value. In a similar fashion, we categorize focal firms (i.e., the firm engaging in reverse engineering) into one of the four product life cycle stages (*Life1* to *Life4*) by identifying the stage that has the highest value for each firm-year. We then take the maximum value among the four life cycle stages (*Life1*, *Life2*, *Life3*, and *Life4*) and categorize the firm-year into the stage that corresponds to the maximum value.[30] We extend Eq. (2) by introducing

[29] For each filing, Hoberg and Maksimovic (2022) create text-based exposures to the four stages of product life cycle as a four-element vector, where each element is bounded between [0, 1] and the four elements sum up to 1.

[30] For example, suppose Apple's TNIC competitors in FY2011 load the highest on *pLife3* compared to *pLife1*, *pLife2*, and *pLife4*. In such case, Apple's TNIC competitors are considered to be in the product maturity stage (*pLife3*) during that year. Further, if Apple in FY2011 has the highest value for *Life1*, compared to *Life2*, *Life3*, or *Life4*, Apple would be categorized as being in the product innovation stage (*Life1*) for that year. Firm-years with tied highest loadings across multiple life cycle stages are excluded from the empirical analysis to ensure unique classification.

interactions between *Peer Trade Secrecy* and the peer firm's product life cycle stage (*pLife1* to *pLife4*), as well as the focal firm's product life cycle stage (*Life1* to *Life4*) in separate regressions. To ease interpretation, we rename the indicator variables as *Product Innovation Stage*, *Process Innovation Stage*, *Product Maturity Stage*, and *Product Decline Stage*, respectively.

Table 8 tabulates the results. In column 1, we find a positive and statistically significant coefficient at the 1% level for *Peer Trade Secrecy* × *Product Innovation Stage*. This finding implies that, when peer firms are innovating, the focal firm is more likely to engage in reverse engineering, especially when trade secrecy is prevalent, suggesting that newly developed products are particularly attractive for reverse engineering, likely because they represent fresh competitive threats. These early-stage targets may also not have sufficient budget to defend themselves legally from reverse engineering efforts. Similarly, we also find a positive and statistically significant coefficient at the 5% level for *Peer Trade Secrecy* × *Process Innovation Stage*, suggesting that peers' process-focused innovations—which are often harder to patent—also invite reverse engineering under high trade secrecy environments. In contrast, we find a negative (but not statistically significant) coefficient for *Peer Trade Secrecy* × *Product Maturity Stage* consistent with the idea that when peers are in the mature stage, their products' technological components are well understood, reducing incentives for reverse engineering.

Column 2 presents the results of interacting *Peer Trade Secrecy* with separate indicators for the focal firm's product life cycle stage. We document a positive and statistically significant coefficient at the 5% (1%) level for the interaction term *Peer Trade Secrecy* × *Product Innovation Stage* (*Process Innovation Stage*). This finding suggests that the relation between secrecy and reverse engineering is magnified for firms in the earlier stages of the product life cycle. These firms face high uncertainty and lack internal knowledge, making them more reliant on reverse engineering to innovate. Intriguingly, we find that the interaction term between *Peer Trade Secrecy* and *Product Decline Stage* is statistically significant at the 5% level (coeff. = 0.0291). This suggests that firms with products in the declining stage may turn to reverse engineering as a lower-cost alternative to extract value from existing market innovations, rather than investing in costly R&D, potentially as a "last-ditch" effort to reposition themselves in the product market.[31]

5. Additional Analysis

5.1 Alternative Measures of Trade Secrecy

We implement robustness checks using alternative measures of trade secrecy. First, we refine our baseline measure of trade secrecy by restricting the TNIC competitors to include only firms that report positive R&D expenditures or have patenting activity and measure *Peer Trade Secrecy (Only Innovators)*.[32] Second, we explore a measure of trade secrecy based on an industry-level survey (Erkens, 2011; Hui et al., 2025). The U.S. Census surveys on an annual basis and queries participants about the significance of trade secrecy in their respective businesses. We extract responses from participants in the Business Research and Development Innovation Survey tables and measure *Peer Trade Secrecy (Survey)* as the proportion of survey respondents who consider trade secrets to be "very important" within the industry.[33] Table 9 Panel A presents the results. In column 1, we find a positive and significant association between trade secrecy and reverse engineering after limiting the TNIC competitors to firms with R&D or patenting activity. In column 2, we continue to find a robust relation using the survey-based measure of trade secrecy. These findings suggest that our main inferences are not sensitive to how we measure trade secrecy.

[31] Hoberg and Maksimovic (2022) document a negative correlation between *Life4* and firms' R&D intensity.
[32] We do not use this approach throughout our empirical analysis given that firms with missing R&D expenses may still conduct R&D activity (e.g., Koh and Reeb, 2015; Glaeser et al., 2025) and patenting only represents successful R&D efforts.
[33] This survey question is available between 2008 and 2015. In untabulated analysis, we document a positive correlation (0.20) between our text-based measure of trade secrecy and the survey-based measure of trade secrecy.

5.2 Alternative Measures of Reverse Engineering

We acknowledge that our primary measure of estimating reverse engineering activities based on abnormal product purchases near corporate headquarters does not *directly* capture the intention behind these purchases. To bolster our inferences, we examine the robustness of our main findings to two alternative measures of reverse engineering.

First, we use a more direct measure of reverse engineering activity by examining legal cases in which firms are accused of reverse engineering competitors' products. Assuming that reverse engineering efforts are successful, a litigation-based measure allows us to directly identify *actual* reverse engineering activities of the firm. We identify all legal cases where the firm is a defendant in such litigations.[34] *# Reverse Engineering Litigations* is defined as the number of litigations initiated during the year where the firm (as a defendant) is accused of reverse engineering.[35] Second, we employ an alternative indirect measure of reverse engineering by analyzing abnormal purchasing behavior near firms' R&D labs. R&D labs are primarily dedicated to innovation-related activities, making them another precise geographic indicator for identifying reverse engineering efforts. We follow Glaeser et al. (2023) and consider R&D labs as 3-digit zip codes that have at least two inventors filing the firm's patents.[36]

Table 9 Panel B presents the results using the two alternative proxies of reverse engineering. In column 1, using a litigation-based measure of reverse engineering, we find a

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[34] We identify such litigations by conducting a comprehensive text search of judicial opinions, rulings, and summaries on Casetext, utilizing keywords such as "reverse engineer" and "reverse engineering." We identify around 100 unique litigations (after manually matching the defendants to public firms).

[35] Because litigation is costly and firms are selective about pursuing legal action, not all reverse engineering efforts result in litigation. Thus, a litigation-based measure likely understates the true prevalence of reverse engineering (i.e., failing to detect instances where reverse engineering occurred but no lawsuit followed).

[36] Inventor locations are sourced from PatentsView. When multiple R&D labs are identified using this procedure, we calculate the weighted average of abnormal product purchases across these locations, using the number of inventors in each 3-digit zip code as weights. This approach assigns greater influence to areas with higher inventor concentrations (e.g., locations indicative of more intensive R&D activities by the firm).

positive and statistically significant coefficient on *Peer Trade Secrecy* (at the 5% level), suggesting that peers' trade secrecy encourages reverse engineering activities. In column 2, we also find that the coefficient on *Peer Trade Secrecy* is positive and statistically significant (at the 1% level) using the R&D labs-based measure of reverse engineering. Overall, these findings demonstrate that our main inferences are robust regardless of how we measure reverse engineering.

5.3 Falsification Test

To further validate that our reverse engineering measure is not simply capturing general consumer demand or unrelated purchasing behavior, we conduct a falsification test using abnormal purchases of non-related products. Specifically, we construct a pseudo dependent variable, *Abn(Purchase of Non-Related Products)*, which captures abnormal purchasing activity in product modules not associated with TNIC competitors' products. The construction mirrors our main measure, but we match the product modules to those unrelated to the focal firm's TNIC competitors. If our main results are driven by broader demand shocks or purchasing trends around the firm's headquarters, we would expect a similar association using this pseudo dependent variable. However, as shown in Table 10, we find no statistically significant relationship between *Peer Trade Secrecy* and the abnormal purchases of non-related products around firms' headquarters. This result supports the interpretation that our reverse engineering measure likely captures targeted, strategic behavior and rules out confounding explanations based on local demand conditions.

6. Conclusion

This paper examines how firms' reverse engineering relates to their competitors' reliance on trade secrecy. We propose a novel measure of reverse engineering activity based on abnormal product purchases near firm headquarters. To validate our proxy, we demonstrate that firms exhibiting greater abnormal purchasing behavior are more likely to introduce products and technologies that more closely resemble competitors' offerings, and is associated with the erosion of peers' gross margins, all of which align with reverse engineering activities. Applying this measure, we find that greater reliance on trade secrecy by competitors leads to increased reverse engineering efforts by firms. This finding is further supported by using the DTSA as a quasi-exogenous shock to peer firm trade secrecy.

Our analysis further shows that this relation is amplified under conditions of heightened proprietary costs and competitive pressure. The relation is also pronounced when rivals are subject to restrictions on employee mobility (via the IDD) and when product market competition intensifies following tariff reductions. Moreover, both the firm's and its peers' positions in the product life cycle play a critical role. Taken together, our findings offer new insights into the costs of trade secrecy and highlight how firm characteristics and market conditions shape the dynamic interplay between trade secrecy and competitive knowledge acquisition.

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Appendix A: Variable Definitions

Variable	Description
Reverse Engineering	The number of peer firm product purchases at the firm's headquarters (measured at the 3-digit zip code) during the quarter, subtracted by the average number of peer firm product purchases in all 3-digit zip codes during the same period. We take the inverse hyperbolic sine transformation for regression analysis.
Reverse Engineering (R&D Lab)	An alternative measure of *Reverse Engineering* using R&D labs as an alternative location of product purchases. R&D labs are identified as 3-digit zip codes that have at least two inventors filing the firm's patents (Glaeser et al., 2023). If a firm has multiple R&D labs, we take the weighted average of the abnormal number of peer firm product purchases, where the weights are the number of inventors in each R&D lab. Data on patent filings are sourced from PatentsView.
# Reverse Engineering Litigations	The number of litigations where the firm (i.e., the defendant) is alleged to have reverse engineered a competitor's product. We manually identify litigations with allegations to reverse engineering from Casetext using a keyword search ("reverse engineer" or "reverse engineering") within all judicial opinions, rulings, and summaries of the litigation.
Peer Trade Secrecy	The percentage of TNIC competitors that possess trade secrets. Firms are considered to possess trade secrets if their public filings mention trade secrets (Glaeser, 2018).
Peer Trade Secrecy (Only Innovators)	The percentage of TNIC competitors engaged in innovation that possess trade secrets. A TNIC competitor is included if it has non-missing R&D expenditures or has filed at least one patent during the sample period. Firms are considered to possess trade secrets if their public filings mention trade secrets (Glaeser, 2018).
Peer Trade Secrecy (Survey)	The proportion of survey respondents who consider trade secrets to be "very important" in the 4-digit NAICS industry. Data is sourced from the Census' Business Research and Development Innovation Survey tables.
Peer Log(1+#Patents Filed)	The natural logarithm of one plus the number of patents filed (Kogan et al., 2017), averaged over all TNIC competitors.
Peer Avg Patent Value	The sum of economic value of patents filed scaled by total assets (Kogan et al., 2017), averaged over all TNIC competitors.
# Trade Secrecy Words	The number of trade secrecy-related words in the firm's public filings following Glaeser (2018).
Post DTSA	An indicator variable that equals one (zero) for firm-quarters that fall in the eight quarters after (before) the passage of DTSA in 2016Q2. For firm-year panel tests, an indicator variable that equals one (zero) for firm-years that fall in the two years after (before) the passage of DTSA in 2016.
Affected States	An indicator variable that equals one for firms headquartered in the state of NY or MA (i.e., the two states that have not adopted the UTSA before 2016), else zero.
% Affected Peers	The percentage of TNIC competitors that are headquartered in the state of NY or MA.
Product Similarity	The average product similarity score between the firm and TNIC competitors (Hoberg and Phillips, 2010; 2016).
Tech Similarity	The average technological similarity between the firm and TNIC competitors (Hoberg and Phillips, 2010; 2016). Technological similarity is measured using the share of patent portfolios that are in the same technological classes following the method in Jaffe and Trajtenberg (1996).
Peer Gross Margin	The median gross margin of the focal firm's TNIC competitors.
Peer % Sales Growth	The median sales growth rate of the focal firm's TNIC competitors.
Peer % COGS Growth	The median cost of goods sold (COGS) growth rate of the focal firm's TNIC competitors.

I (Signif. Tariff Reduction)	An indicator variable that equals one if the firm's industry experiences a significant tariff reduction in the prior year, else zero. A tariff reduction is considered as significant if the three-digit SIC level tariff decreases relative to the prior year by more than three times the median tariff rate decrease and is not preceded or followed by a tariff increase of equivalent magnitude (Frésard 2010). Data on industry-level tariffs (i.e., *ad valorem* most favored nation tariff rate) are collected from the USITC. Following Glaeser and Landsman (2019), we use the crosswalk file developed by Pierce and Schott (2012) to link HTS8 classifications to the three-digit SIC level.
High % of IDD Peers	An indicator variable that equals one for above-median observations of *% of IDD Peers*. *% of IDD Peers* is defined as percentage of TNIC competitors that are headquartered in states that adopted the Inevitable Disclosure Doctrine (IDD) following Klasa et al. (2018). The states (abbreviated) are the following: AR, CT, DE, GA, IL, IN, IA, KS, MA, MI, MN, MO, NJ, NY, NC, OH, PA, UT, WA. All states have adopted the IDD before the beginning of our sample period (2006).
Product Innovation Stage	An indicator variable that equals one if the firm (or TNIC competitors of the firms) is in the product innovation stage, else zero. Firm-years with the highest value of *Life1* (or *pLife1*) is considered as those in the product innovation stage (Hoberg and Maksimovic, 2022).
Process Innovation Stage	An indicator variable that equals one if the firm (or TNIC competitors of the firms) is in the process innovation stage, else zero. Firm-years with the highest value of *Life2* (or *pLife2*) is considered as those in the process innovation stage (Hoberg and Maksimovic, 2022).
Product Maturity Stage	An indicator variable that equals one if the firm (or TNIC competitors of the firms) is in the product maturity stage, else zero. Firm-years with the highest value of *Life3* (or *pLife3*) is considered as those in the product maturity stage (Hoberg and Maksimovic, 2022).
Product Decline Stage	An indicator variable that equals one if the firm (or TNIC competitors of the firms) is in the product decline (discontinuation) stage, else zero. Firm-years with the highest value of *Life4* (or *pLife4*) is considered as those in the product decline (discontinuation) stage (Hoberg and Maksimovic, 2022).
Peer Vague Patents	The percentage of patents by peer firms that contains vague language. A patent is classified as containing vague language if its description text includes at least one of the following terms or phrases (following Arinas, 2012): *Alternate(ly)*, *Alternative(ly), Another*, *Still further*, *A further*, *Illustrative*, *A predetermined*, *A preferred*, *Still another*, *Yet another*, *broad, Embodiment/aspect of the present invention, Invention/disclosure/present invention is not limited by, In this respect/Thereto, The present disclosure/invention* or *This invention relates, Generally/In general to, At least*, *Ranging from*, *Preferably*, *Preferred*, *A plurality/ratio/set/subset/member/section/mixture/segment of*, *Portions of*, *Components of*, *Embodiments of, May/can (also) be, Substantially/Selectively*. Patents are matched to industries following Kim and Valentine (2023) using the crosswalk file by Goldschlag et al. (2016).
Abn(Purchase of Non-Related Products)	The number of non-related product purchases at the firm's headquarters (measured at the 3-digit zip code) during the quarter, subtracted by the average number of non-related product purchases in all 3-digit zip codes during the same period. We take the inverse hyperbolic sine transformation for regression analysis. Non-related products are defined as all product modules not matched to the focal firm's TNIC competitors during the firm-to-product mapping procedure described in Section 3.
Size	The natural logarithm of total assets.
R&D / Assets	Research and development (R&D) expense scaled by total assets.
Log(1+#Patents Filed)	The natural logarithm of one plus the number of patents filed (Kogan et al., 2017).

Avg Patent Value	The sum of economic value of patents filed scaled by total assets (Kogan et al., 2017).
ROA	Income before income taxes scaled by total assets.
SG&A / Sales	Selling, general, and administrative (SG&A) expense scaled by total sales.
Firm Age	The reciprocal of one plus the number of years the firm has been on the Compustat database multiplied by (-1) (Pastor and Pietro, 2003).
HHI	The Herfindahl-Hirschman Index, defined as the sum of squared market shares (based on sales) of the 2-digit SIC industry.
Leverage	Book value of financial leverage, defined as long term debt plus debt in current liabilities scaled by total assets.

Figure 1: Measuring Reverse Engineering

This figure presents an illustration of how we create *Reverse Engineering* using example firms. Cardinal Health is a Compustat firm with a TNIC peer in the Neilsen Scanner database (McKesson). We begin by identifying all product modules sold by McKesson. For simplicity, suppose McKesson sells in four different product modules (8425 – Cough Syrups & Tablets; 8502 – Sinus Remedies; 8522 – Dental Floss; and 8530 – First Aid Thermometers). We then calculate the total purchase volume for these product modules in the (3-digit) zip code area surrounding Cardinal Health's headquarters during a given quarter, scaled by the local population. We then normalize this measure using the average purchase volume of the product modules in all (3-digit) zip codes during the same period.

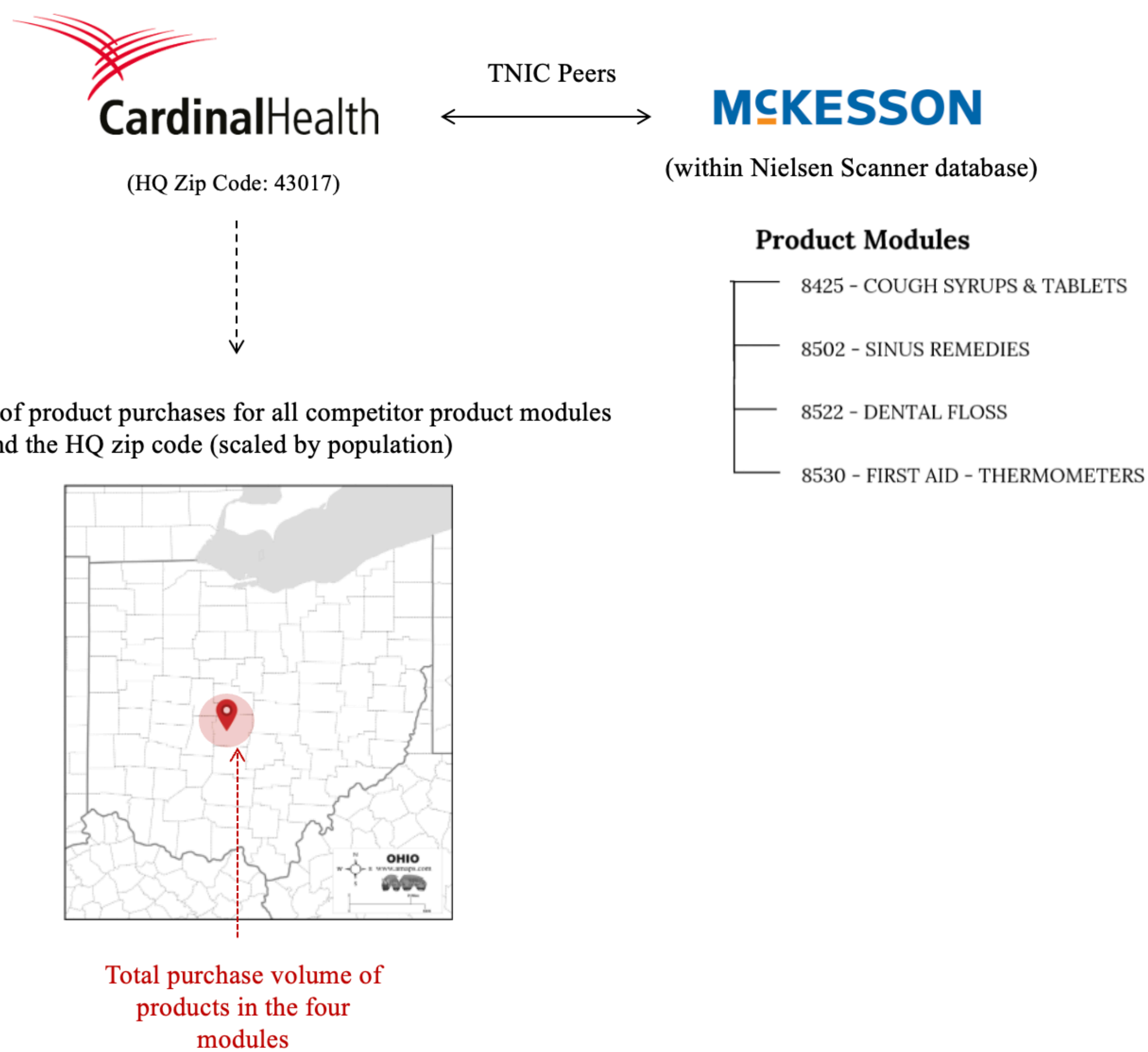


Figure 2: Abnormal Product Purchases around Firm HQ and New Product Market Entry

This figure compares abnormal product purchases near the headquarters of firms entering a new product market (i.e., blue line) with those of control firms (i.e., red line). We plot monthly trends from 48 months before to 48 months after the entry to a new product market, defined as the first instance of a product announcement in the new market ($t = 0$). Each series displays the average volume of product purchases near the headquarters of firms, adjusted by the average volume of product purchases in all (3-digit) zip codes during the same period. The volume of product purchases is scaled by the (3-digit) zip code's population. The vertical dashed line marks the timing of the product announcement. The control firms are defined as TNIC competitors of the focal firm that i) do not enter the new product market, and ii) are headquartered in a different (3-digit) zip code as the focal firm.

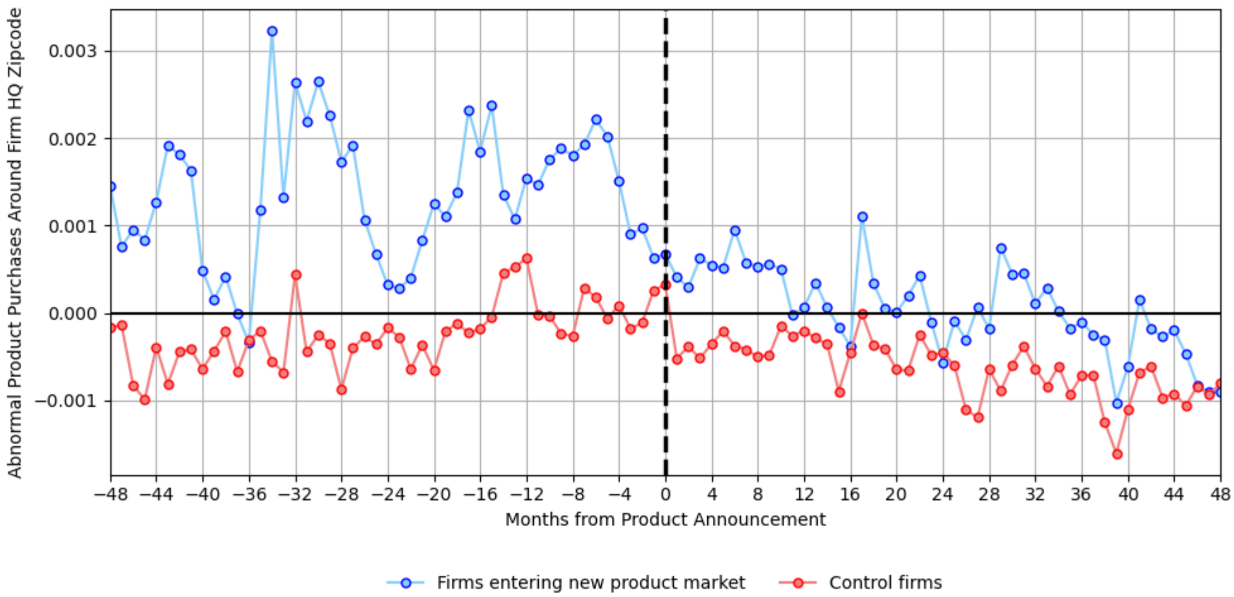
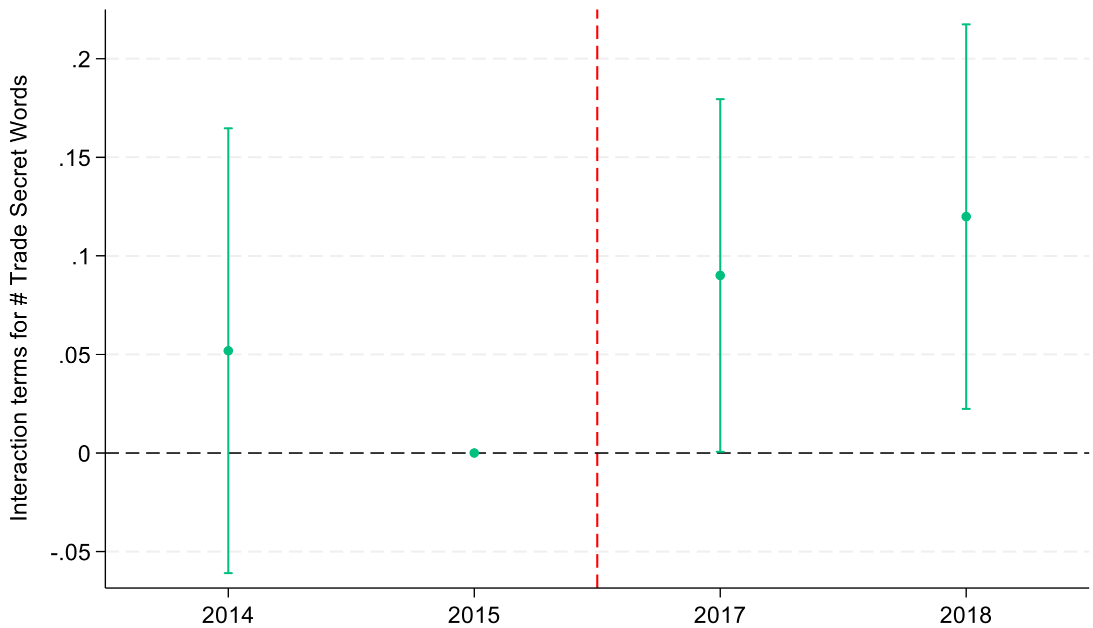


Figure 3: Pre-Trends of Defend Trade Secrets Act (DTSA)

This figure presents pre-trend analyses for Table 4. For Panel A, we replace *Post DTSA* with indicator variables for each year (with 2015 as the baseline and omitted). For Panel B, we replace *Post DTSA* with indicator variables for each quarter (with quarters before 2015Q2 and quarters after 2017Q2 grouped together). The indicator for the quarters before 2015Q1 is used as the baseline and omitted. Each regression includes the respective fixed effects and clusters at the industry-year level. We plot the coefficient value for the interaction terms and their 95% confidence interval over for each regression.

Panel A: Effect of DTSA on Trade Secrecy



Panel B: Effect of DTSA on Reverse Engineering

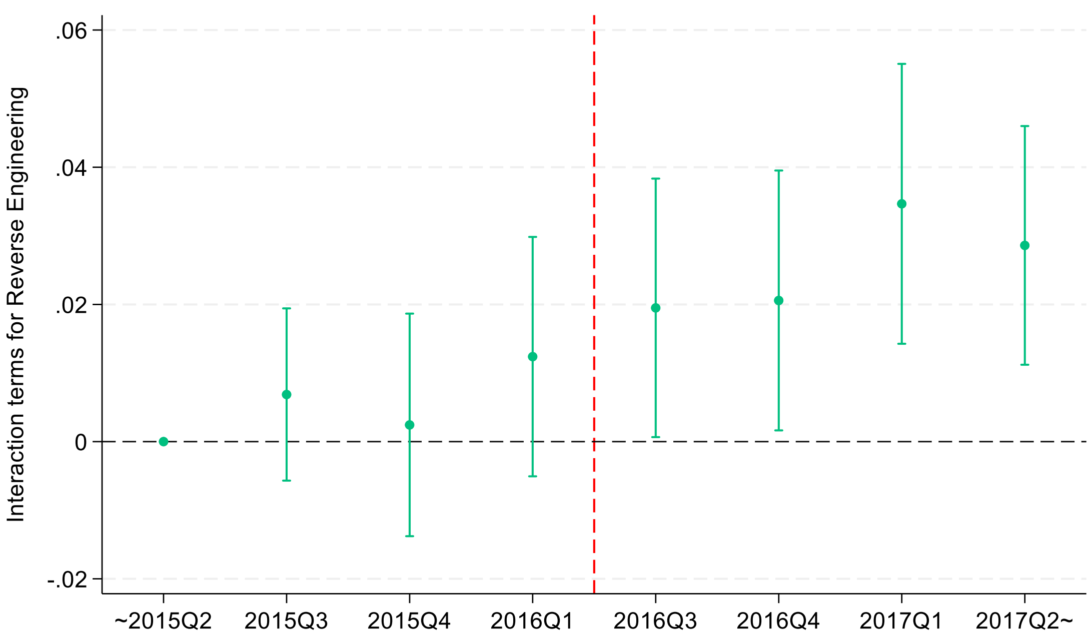


Table 1: Sample Selection

This table illustrates the sample selection procedure. We first begin with a sample of 515 public companies whose product UPCs are matched to the Nielsen scanner database. We identify a total of 6,334 product market competitors of these 515 public companies based on the firm's text-based network industry (TNIC). We next remove 1,346 firms without headquarter zip code data to construct our geography-based measure of reverse engineering. We next remove 735 financial firms (i.e., 4-digit SIC industries: 6000-6999). We lastly remove 685 firms without data on control variables. Our main sample encompasses 3,568 unique firms over the period 2006-2020.

	# Firms	# Product Modules	# Peers
# of firms matched to Nielsen scanner database	515	1,126	
# of peer firms identified based on TNIC			6,334
Less: Firms without headquarter data			(1,346)
Less: Financial firms (SIC 6000-6999)			(735)
Less: Firms with non-missing control variables			(685)
Main sample			3,568

Table 2: Descriptive Statistics

This table illustrates the descriptive statistics of our panel. Panel A presents the summary statistics of the variables used in our analyses. Panel B presents the most common industries in our sample (based on 4-digit SIC industries) alongside the mean and median values of *Reverse Engineering*.

Panel A: Main Sample

Variable	Mean	Std	P25	P50	P75
Reverse Engineering	0.038	0.083	0.005	0.036	0.078
Peer Trade Secrecy	0.681	0.326	0.350	0.857	0.967
Peer Log(1+#Patents Filed)	0.513	0.528	0.045	0.383	0.791
Peer Avg Patent Value	0.025	0.025	0.001	0.020	0.041
Peer Vague Patents	0.041	0.008	0.037	0.042	0.045
% Affected Peers	0.142	0.121	0.031	0.133	0.225
Peer Trade Secrecy (Only Innovators)	0.703	0.318	0.400	0.889	0.971
Peer Trade Secrecy (Survey)	0.349	0.239	0.170	0.210	0.594
Size	6.352	2.038	4.860	6.263	7.773
R&D / Assets	0.024	0.039	0.000	0.005	0.032
Log(1+#Patents Filed)	0.521	0.999	0.000	0.000	0.693
Avg Patent Value	0.021	0.047	0.000	0.000	0.016
ROA	-0.018	0.074	-0.022	0.006	0.020
SG&A / Sales	0.375	0.438	0.098	0.267	0.479
Firm Age	-0.082	0.067	-0.111	-0.059	-0.037
HHI	0.023	0.020	0.010	0.015	0.028
Leverage	0.211	0.220	0.002	0.161	0.340
Product Similarity	0.072	0.064	0.023	0.051	0.099
Tech Similarity	0.520	0.348	0.197	0.542	0.855
Peer Gross Margin	0.357	0.319	0.261	0.383	0.537

Panel B: Industry Distribution

SIC4 Industry	% of Sample	Reverse Engineering	
		Mean	Median
2834 - Pharmaceutical Preparations	6.21%	0.030	0.046
2836 - Biological Products, Except Diagnostic Substances	4.50%	0.036	0.052
7372 - Prepackaged Software	4.27%	0.031	0.024
3674 - Semiconductors and Related Devices	3.53%	0.075	0.076
7370 - Computer Programming, Data Processing, and Other Computer Related Services	2.81%	0.020	0.019
1311 - Crude Petroleum and Natural Gas	2.77%	0.058	0.087
3841 - Surgical and Medical Instruments and Apparatus	2.73%	0.054	0.048
5812 - Eating Places	2.57%	0.084	0.085
2830 - Drugs	2.17%	0.023	0.031
3670 - Electronic Components and Accessories	2.09%	0.076	0.074
8731 - Commercial Physical and Biological Research	1.55%	0.041	0.039
3845 - Electromedical and Electrotherapeutic Apparatus	1.45%	0.060	0.056
7389 - Business Services, Not Elsewhere Classified	1.42%	0.025	0.006
1382 - Oil and Gas Field Exploration Services	1.40%	0.029	0.083
3840 - Surgical, Medical, and Dental Instruments and Supplies	1.29%	0.035	0.038
7371 - Computer Programming Services	1.04%	0.014	0.008
All other industries (each ≤1%)	58.20%	0.035	0.034

Table 3: Validation of the Reverse Engineering Measure

This table presents validation test results by examining whether abnormal product purchasing activity around firm headquarters predicts outcomes consistent with reverse engineering activities. In Panel A, we examine the relation between abnormal product purchasing activity around firm headquarters and five innovation and product market outcomes in the following year: (i) *Product Similarity*, (ii) *Tech Similarity*, (iii) *R&D / Assets*, and (iv) *Log(1+#Patents Filed)*. *Product Similarity* is defined as the average product similarity score between the firm and the peer firms in the same text-based network industry. *Tech Similarity* is defined as the average technological similarity between the firm and peer firms in the same text-based network industry (Jaffe and Trajtenberg, 1996). *R&D / Assets* is defined as R&D expense scaled by total assets. *Log(1+#Patents Filed)* is defined as the natural logarithm of one plus the number of patents filed (Kogan et al., 2017). In Panel B, we examine the relation between abnormal product purchasing activity around firm headquarters and gross margin erosion of peer firms in the same text-based network industry as the focal firm. In column 1, the dependent variable is *Peer Gross Margin*, defined as the median gross margin of peer firms. In column 2, the dependent variable is *Peer % Sales Growth*, defined as the median sales growth rate of peer firms. In column 3, the dependent variable is *Peer % COGS Growth*, defined as the median cost of goods sold (COGS) growth rate of peer firms. For both panels, the variable of interest is the decile-ranked *Reverse Engineering*, defined as the number of peer firm product purchases at the firm's headquarters (measured at the 3-digit zip code) during the year, subtracted by the average number of peer firm product purchases in all 3-digit zip codes during the same period. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix A. Standard errors are clustered at the industry-year level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Innovation and Product Market Outcomes

	(1)	(2)	(3)	(4)
Dep. Var. =	Product Similarity$_{t+1}$	Tech Similarity$_{t+1}$	R&D / Assets$_{t+1}$	Log(1+#Patents Filed)$_{t+1}$
Reverse Engineering (Deciled)	0.0035	0.0267	0.0104	0.0562
	[2.97]***	[1.82]*	[3.03]***	[1.78]*
Size	0.0029	0.0180	-0.0110	0.0582
	[6.31]***	[2.56]**	[-5.41]***	[5.29]***
R&D / Assets	0.0020	0.0308	0.4205	0.6920
	[0.17]	[0.17]	[5.30]***	[2.73]***
Log(1+#Patents Filed)	0.0006	0.0028	0.0016	0.2148
	[1.58]	[0.54]	[0.89]	[11.00]***
Avg Patent Value	0.0208	0.0255	-0.0829	-0.4818
	[3.61]***	[0.39]	[-2.57]**	[-2.43]**
ROA	-0.0044	0.0698	0.0565	0.0716
	[-1.02]	[0.97]	[2.26]**	[0.81]
SG&A / Sales	0.0002	0.0115	-0.0015	-0.0091
	[0.31]	[1.96]*	[-0.57]	[-1.16]
Firm Age	-0.0093	0.0980	0.0089	0.0888
	[-2.27]**	[0.99]	[0.78]	[1.00]
HHI	0.0055	-0.4190	-0.0451	1.5833
	[0.18]	[-0.64]	[-0.83]	[2.88]***
Leverage	-0.0011	0.0107	-0.0224	-0.0889
	[-0.77]	[0.43]	[-2.76]***	[-2.97]***
Observations	18,613	5,868	18,719	18,719
Adjusted R-squared	0.9184	0.6651	0.8112	0.8876
Firm & Year FE	Yes	Yes	Yes	Yes

Panel B: Peers' Gross Margin Erosion

Dep. Var. =	(1) Peer Gross $Margin_{t+1}$	(2) Peer % Sales $Growth_{t+1}$	(3) Peer % COGS $Growth_{t+1}$
Reverse Engineering (Deciled)	-0.0313	-0.0133	-0.0041
	[-3.48]***	[-1.72]*	[-0.48]
Size	-0.0029	-0.0041	-0.0061
	[-0.64]	[-1.38]	[-2.50]**
R&D / Assets	0.2203	-0.0189	-0.0476
	[2.42]**	[-0.56]	[-2.28]**
Log(1+#Patents Filed)	0.0025	0.0031	0.0043
	[0.65]	[1.59]	[2.73]***
Avg Patent Value	-0.0583	0.0006	0.0158
	[-1.83]*	[0.06]	[1.59]
ROA	-0.0015	-0.0268	0.0097
	[-0.05]	[-1.42]	[0.92]
SG&A / Sales	-0.0000	0.0000	0.0000
	[-3.23]***	[0.48]	[0.75]
Firm Age	-0.0284	-0.0194	-0.0234
	[-0.89]	[-0.67]	[-0.49]
HHI	-0.0962	-0.0671	-0.0222
	[-0.93]	[-0.37]	[-0.17]
Leverage	-0.0267	-0.0086	-0.0015
	[-1.95]*	[-1.55]	[-0.29]
Observations	18,737	18,737	18,737
Adjusted R-squared	0.7612	0.2891	0.3139
Firm & Year FE	Yes	Yes	Yes

Table 4: Reverse Engineering and Trade Secrecy

This table examines the relation between trade secrecy and reverse engineering. Panel A (B) examines the relation between competitors' use of trade secrecy (patents) and reverse engineering. The dependent variable is *Reverse Engineering*, defined as the number of peer firm product purchases at the firm's headquarters (measured at the 3-digit zip code) during the quarter, subtracted by the average number of peer firm product purchases in all 3-digit zip codes during the same period. We take the inverse hyperbolic sine transformation of *Reverse Engineering*. In Panel A, the variable of interest is *Peer Trade Secrecy*, defined as the percentage of TNIC competitors that possess trade secrets, measured using the Glaeser (2018) method. In Panel B, the variable of interest is one of the following: *Peer Log(1+#Patents Filed)*, *Peer Avg Patent Value*, or *Peer Vague Patents*. *Peer Log(1+#Patents Filed)* is defined as the natural logarithm of one plus the number of patents filed, averaged over all TNIC competitors. *Peer Avg Patent Value* is defined as the sum of economic value of patents filed scaled by total assets, averaged over all TNIC competitors. *Peer Vague Patents* is defined as the percentage of patents by peer firms that contains vague language (i.e., one of the following words or phrases in the Arinas [2012] list). Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix A. Standard errors are clustered at the industry-year level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Reverse Engineering and Peer Trade Secrecy

	(1)	(2)	(3)
	Dep. Var. = Reverse Engineering		
Peer Trade Secrecy	0.0065	0.0057	0.0060
	[2.36]**	[2.83]***	[2.93]***
Size			-0.0003
			[-0.37]
R&D / Assets			0.0012
			[0.08]
Log(1+#Patents Filed)			-0.0004
			[-0.60]
Avg Patent Value			-0.0094
			[-1.02]
ROA			0.0066
			[1.35]
SG&A / Sales			0.0001
			[0.08]
Firm Age			0.0136
			[1.22]
HHI			-0.2237
			[-3.43]***
Leverage			0.0090
			[3.20]***
Observations	75,963	75,963	75,963
Adjusted R-squared	0.0006	0.7879	0.7882
Firm FE	No	Yes	Yes
YearQtr FE	No	Yes	Yes

Panel B: Reverse Engineering and Peer Patenting Activity

	(1)	(2)	(3)
	Dep. Var. = Reverse Engineering		
Peer Log(1+#Patents Filed)	-0.0117		
	[-7.55]***		
Peer Avg Patent Value		-0.1824	
		[-5.81]***	
Peer Vague Patents			0.1831
			[3.54]***
Controls	Yes	Yes	Yes
Observations	75,963	75,963	66,790
Adjusted R-squared	0.7889	0.7887	0.7901
Firm & YearQtr FE	Yes	Yes	Yes

Table 5: Defend Trade Secrets Act (DTSA) as a Shock to Trade Secrecy

This table exploits the adoption of the Defend Trade Secrets Act (DTSA) as a quasi-exogenous shock to trade secrecy. Panel A presents the results of the validation test. The dependent variable is *# Trade Secrecy Words*, defined as the number of trade secrecy words in the firm's public filings following Glaeser (2018). We estimate a Poisson regression (Cohn et al., 2022). The variable of interest is the interaction term *Post DTSA × Affected States*. *Post DTSA* is an indicator variable that equals one (zero) for observations that fall in 2017 or 2018 (2014 or 2015). *Affected States* is an indicator variable that equals one for firms headquartered in the state of NY or MA, else zero. Panel B examines the relation between trade secrecy and reverse engineering. The dependent variable is *Reverse Engineering*, defined as the number of peer firm product purchases at the firm's headquarters (measured at the 3-digit zip code) during the quarter, subtracted by the average number of peer firm product purchases in all 3-digit zip codes during the same period. We take the inverse hyperbolic sine transformation of *Reverse Engineering*. The variable of interest is the interaction term *Post DTSA × % Affected Peers*. For this panel, *Post DTSA* is an indicator variable that equals one for firm-quarters that fall in the eight quarters after (before) the passage of DTSA in 2016Q2. *% Affected Peers* is the percentage of TNIC competitors that are headquartered in the state of NY or MA. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix A. Standard errors are clustered at the industry-year level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Validation (Effect of DTSA on Trade Secrecy)

	(1)	(2)
	Dep. Var. = # Trade Secrecy Words	
Post DTSA × Affected States	0.0738	0.0815
	[1.83]*	[2.11]**
Controls	No	Yes
Observations	4,996	4,996
Pseudo R-squared	0.5445	0.5451
Firm & Year FE	Yes	Yes

Panel B: Effect of DTSA on Reverse Engineering

	(1)	(2)
	Dep. Var. = Reverse Engineering	
Post DTSA × % Affected Peers	0.0238	0.0234
	[3.60]***	[3.57]***
Controls	No	Yes
Observations	16,138	16,138
Adjusted R-squared	0.8996	0.8996
Firm & YearQtr FE	Yes	Yes

Table 6: Reverse Engineering and Trade Secrecy – Product Market Competition

This table examines whether the relation between trade secrecy and reverse engineering is more pronounced under heightened product market competition proxied by a significant tariff reduction in the industry The dependent variable is *Reverse Engineering*, defined as the inverse hyperbolic sine of the number of peer firm product purchases at the firm's headquarters (measured at the 3-digit zip code) during the quarter, subtracted by the average number of peer firm product purchases in all 3-digit zip codes during the same period. *Peer Trade Secrecy* is defined as the percentage of TNIC competitors that possess trade secrets, measured using the Glaeser (2018) method. The variable of interest is the interaction term *Peer Trade Secrecy × I (Signif. Tariff Reduction)*. *I (Signif. Tariff Reduction)* is defined as an indicator variable that equals one if the firm's industry experiences a significant tariff reduction in the prior year, else zero. A tariff reduction is considered as significant if the three-digit SIC level tariff decreases relative to the prior year by more than three times the median tariff rate decrease and is not preceded or followed by a tariff increase of equivalent magnitude (Frésard 2010). Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix A. Standard errors are clustered at the industry-year level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1) Dep. Var. = Reverse Engineering
Peer Trade Secrecy	0.0055
	[2.67]***
I (Signif. Tariff Reduction)	-0.0057
	[-1.80]*
Peer Trade Secrecy × I (Signif. Tariff Reduction)	0.0084
	[1.81]*
Size	-0.0003
	[-0.37]
R&D / Assets	0.0013
	[0.09]
Log(1+#Patents Filed)	-0.0004
	[-0.60]
Avg Patent Value	-0.0091
	[-0.99]
ROA	0.0066
	[1.36]
SG&A / Sales	0.0001
	[0.09]
Firm Age	0.0137
	[1.22]
HHI	-0.2259
	[-3.46]***
Leverage	0.0090
	[3.19]***
Observations	75,963
Adjusted R-squared	0.7882
Firm & YearQtr FE	Yes

Table 7: Reverse Engineering and Trade Secrecy – Talent-Based Knowledge Acquisition

This table examines whether the relation between trade secrecy and reverse engineering is more pronounced when talent-based knowledge acquisition is more costly. We use the percentage of TNIC competitors that are headquartered in states adopting the Inevitable Disclosure Doctrine (IDD) to proxy for firms facing limitations on the ability to hire rivals' employees. The dependent variable is *Reverse Engineering*, defined as the inverse hyperbolic sine of the number of peer firm product purchases at the firm's headquarters (measured at the 3-digit zip code) during the quarter, subtracted by the average number of peer firm product purchases in all 3-digit zip codes during the same period. *Peer Trade Secrecy* is defined as the percentage of TNIC competitors that possess trade secrets, measured using the Glaeser (2018) method. The variable of interest is the interaction term *Peer Trade Secrecy* × *High % of IDD Peers*. *High % of IDD Peers* is defined as an indicator variable that equals one if the percentage of TNIC competitors that are headquartered in states that adopted the IDD is above the sample median, else zero. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix A. Standard errors are clustered at the industry-year level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1) Dep. Var. = Reverse Engineering
Peer Trade Secrecy	0.0039
	[1.78]*
High % of IDD Peers	-0.0022
	[-1.20]
Peer Trade Secrecy × High % of IDD Peers	0.0050
	[2.12]**
Size	-0.0004
	[-0.41]
R&D / Assets	0.0007
	[0.04]
Log(1+#Patents Filed)	-0.0003
	[-0.58]
Avg Patent Value	-0.0095
	[-1.03]
ROA	0.0063
	[1.29]
SG&A / Sales	0.0001
	[0.05]
Firm Age	0.0115
	[1.02]
HHI	-0.2239
	[-3.44]***
Leverage	0.0089
	[3.15]***
Observations	75,963
Adjusted R-squared	0.7883
Firm & YearQtr FE	Yes

Table 8: Reverse Engineering and Trade Secrecy – Product Life Cycle

This table examines whether the relation between trade secrecy and reverse engineering varies over the product life cycle. The dependent variable is *Reverse Engineering*, defined as the inverse hyperbolic sine of the number of peer firm product purchases at the firm's headquarters (measured at the 3-digit zip code) during the quarter, subtracted by the average number of peer firm product purchases in all 3-digit zip codes during the same period. The variable of interest is the four interaction terms between *Peer Trade Secrecy* and *Product Innovation Stage*, *Process Innovation Stage*, *Product Maturity Stage*, and *Product Decline Stage*, respectively. *Peer Trade Secrecy* is defined as the percentage of TNIC competitors that possess trade secrets, measured using the Glaeser (2018) method. We assign each firm-year observation to a single product life cycle stage based on the methodology from Hoberg and Maksimovic (2022). Specifically, each firm is assigned a loading on four latent product life cycle dimensions (*Life1* to *Life4*). For focal firms, we identify the stage corresponding to the highest loading in a given year and create indicators for: *Product Innovation* (*Life1*), *Process Innovation* (*Life2*), *Product Maturity* (*Life3*), and *Product Decline* (*Life4*). For TNIC peer firms (i.e., firms being reverse engineered), we average the *Life1–Life4* loadings across peers and assign the competitor group to the stage with the highest average loading (*pLife1–pLife4*), similarly defining stage indicators. In column 1 (2), product life cycle stages are based on peer firm (focal firm) classifications. The coefficient for *Product Decline Stage* is omitted due to multicollinearity. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix A. Standard errors are clustered at the industry-year level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Product life cycle of:	Peer Firms	Focal Firm
	(1)	(2)
	Dep. Var. = Reverse Engineering	
Peer Trade Secrecy × Product Innovation Stage	0.0266	0.0152
	[3.40]***	[2.11]**
Peer Trade Secrecy × Process Innovation Stage	0.0110	0.0122
	[2.45]**	[3.06]***
Peer Trade Secrecy × Product Maturity Stage	-0.0075	0.0051
	[-1.43]	[1.00]
Peer Trade Secrecy × Product Decline Stage	0.0174	0.0291
	[0.72]	[2.37]**
Product Innovation Stage	-0.0145	0.0020
	[-0.78]	[0.19]
Process Innovation Stage	-0.0041	0.0098
	[-0.24]	[1.15]
Product Maturity Stage	0.0065	0.0154
	[0.37]	[1.63]
Controls	Yes	Yes
Observations	71,749	72,022
Adjusted R-squared	0.8075	0.8068
Firm & YearQtr FE	Yes	Yes

Table 9: Robustness Tests

This table presents robustness tests. Panel A examines the relation between alternative measures of trade secrecy and reverse engineering. The dependent variable is *Reverse Engineering*, defined as the number of peer firm product purchases at the firm's headquarters (measured at the 3-digit zip code) during the quarter, subtracted by the average number of peer firm product purchases in all 3-digit zip codes during the same period. We take the inverse hyperbolic sine transformation of *Reverse Engineering*. In column 1, the variable of interest is *Peer Trade Secrecy (Only Innovators)*, defined analogously as *Peer Trade Secrecy* but constrained to peers with R&D expense or patenting activity. In column 2, the variable of interest is *Peer Trade Secrecy (Survey)*, defined as the proportion of survey respondents who consider trade secrets to be "very important" within the industry. Panel B examines the relation between trade secrecy and alternative proxies of reverse engineering. In column 1, we use a litigation-based proxy for reverse engineering. *# Reverse Engineering Litigations* is the number of litigations where the firm (i.e., defendant) is alleged to have reverse engineered a competitor's product. We estimate a Poisson regression (Cohn et al., 2022). In column 2, we use R&D labs (i.e., 3-digit zip codes that have at least two inventors filing the firm's patents) as an alternative location of product purchases. *Reverse Engineering (R&D Labs)* is defined as the inverse hyperbolic sine of the number of peer firm product purchases at the firm's R&D labs (measured at the 3-digit zip code) subtracted by the average number of peer firm product purchases in all 3-digit zip codes during the same period. If a firm has multiple R&D labs, we take the weighted average of the abnormal number of peer firm product purchases, where the weights are the number of inventors in each R&D lab. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix A. Standard errors are clustered at the industry-year level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Alternative Measures of Trade Secrecy

	(1)	(2)
	Dep. Var. = Reverse Engineering	
Peer Trade Secrecy (Only Innovators)	0.0058	
	[3.05]***	
Peer Trade Secrecy (Survey)		0.0151
		[4.48]***
Controls	Yes	Yes
Observations	75,963	40,849
Adjusted R-squared	0.7882	0.8380
Firm & YearQtr FE	Yes	Yes

Panel B: Alternative Measures of Reverse Engineering

	(1)	(2)
Dep. Var. =	# Reverse Engineering Litigations	Reverse Engineering (R&D Lab)
Peer Trade Secrecy	1.8808	0.0096
	[2.04]**	[2.92]***
Controls	Yes	Yes
Observations	19,541	28,059
Pseudo R-squared	0.6117	-
Adjusted R-squared	-	0.7744
Firm & Year FE	Yes	-
Firm & YearQtr FE	-	Yes

Table 10: Falsification Test

This table presents a falsification test. The dependent variable is *Abn(Purchase of Non-Related Products)*, defined as the number of non-related product purchases at the firm's headquarters (measured at the 3-digit zip code) during the quarter, subtracted by the average number of non-related product purchases in all 3-digit zip codes during the same period. We take the inverse hyperbolic sine transformation of *Abn(Purchase of Non-Related Products)*. Non-related products are defined as all product modules not matched to the focal firm's TNIC competitors during the firm-to-product mapping procedure described in Section 3. The variable of interest is *Peer Trade Secrecy*, defined as the percentage of TNIC competitors that possess trade secrets, measured using the Glaeser (2018) method. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix A. Standard errors are clustered at the industry-year level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	Dep. Var. =	(1) Abn(Purchase of Non-Related Products)
Peer Trade Secrecy		0.0004
		[0.93]
Controls		Yes
Observations		75,963
Adjusted R-squared		0.8773
Firm & YearQtr FE		Yes