When trust breaks: academic misconduct, innovation networks, and capital discrimination

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Abstract

We investigate how trust shocks affect innovation networks through an incomplete contracting framework. Using academic misconduct cases in China (2015-2021) as an identification strategy, we construct a comprehensive dataset combining patent activities and venture capital investments. We document three key findings. First, academic misconduct triggers persistent declines in university-industry collaboration, reducing both joint patents and citations to university research. Second, affected firms strategically shift toward inter-firm R&D alliances. This substitution decreases patent basicness but increases product orientation. Third, trust shocks propagate to capital markets, with venture capitalists reducing investments in firms previously linked to universities involved in misconduct. Our findings highlight trust as an irreplaceable mechanism in innovation governance and demonstrate how trust breakdowns reconfigure contractual relationships and resource allocation in innovation networks.

Keywords: Academic misconduct, Innovation networks, Trust, Incomplete contracts, Venture capital

JEL Classification: G39, O31, G24, D86, L14

1 Introduction

Innovation partnerships face unique contractual challenges due to their inherent uncertainty and complexity(Aghion and Tirole, 1994; Francois and Roberts, 2003; Xie et al., 2022). Although formal mechanisms such as monitoring and incentive schemes can address these challenges, such solutions often prove prohibitively costly in innovation settings (Holmstrom, 1989; Manso, 2011). In response, firms increasingly rely on trust as an informal mechanism to reduce transaction costs, minimize monitoring needs, and mitigate information asymmetries between partners(Williamson, 1993; Carlin et al., 2009).

Trust, a core element of social capital (Glaeser et al., 2000; Xie et al., 2022), shapes organizational interaction patterns and enables various forms of inter-organizational partnerships, from venture capital investments to research collaborations (McEvily et al., 2003; Nanda and Rhodes-Kropf, 2018). This coordination function becomes particularly vital in university-industry collaboration (UIC), where universities serve as primary sources of knowledge creation in innovation networks. However, fundamental organizational differences create inherent tensions: universities prioritize open research and academic breakthroughs, while firms focus on commercial value and proprietary development (Rosenberg and Nelson, 1994; Aghion et al., 2008). Trust helps bridge these institutional barriers by fostering shared expectations and reducing formal contracting costs (Aghion and Tirole, 1994; Xie et al., 2022).

While prior research has focused on trust's facilitative role in collaboration, how trust breakdown reshapes innovation networks remains poorly understood. This gap warrants attention for three reasons. First, distinct from technological or competitive shocks, trust breaches directly undermine the core mechanism that sustains innovation partnerships. Second, such shocks destabilize the broader informal governance structure that compensates for contractual limitations in innovation networks. Third, despite the growing importance of UIC for breakthrough innovations(Hsu et al., 2024), we lack evidence on the resilience of these partnerships during trust crises. We address this gap by examining academic misconduct as a trust shock, investigating its impact through three channels: firms' restructuring of R&D partnerships, changes in innovation characteristics, and shifts in venture capital allocation.

To investigate these questions, we construct a comprehensive dataset of academic misconduct cases, patent activities, and Venture Capital (VC) investments in China from 2010 to 2021. Our dataset combines 134 academic misconduct cases across six disciplines [1] from the National Natural Science Foundation of China (NNSFC) with over 18 million patent applications from the China National Intellectual Property Administration (CNIPA) and their Google Patents citation records. We complement this with VC

[1]Six disciplines include Information Sciences, Medical Sciences, Engineering and Materials Sciences, Life Sciences, Earth Sciences, and Chemistry, see appendix Table A.1

investment data from PEDATA, covering over 100,000 investments during our sample period.

Our analysis spans three levels. At the city-industry level, we track changes in firm-to-university patent citations and joint patents following misconduct exposure. At the pair level, we examine the strategic adjustments of firms between university and corporate R&D partnerships. At the firm level, we analyze changes in innovation characteristics and VC investment patterns.

China provides an ideal setting for studying trust shocks in innovation networks for several reasons. First, rapid growth in UIC and strengthening intellectual property protection have created high-stakes trust relationships vulnerable to misconduct shocks (Chen et al., 2016).[2] Second, the basic research infrastructure in China remains relatively weak and commercialization faces substantial barriers, making trust particularly critical for innovation partnerships.[3] Third, strong geographical barriers in knowledge spillovers, driven by transportation costs and regional development heterogeneity (Hong and Su, 2013), increase the importance of local university-industry relationships. The substantial variation in regional innovation systems, with local factors explaining 15-25% of university research commercialization outcomes (Lerner et al., 2024), offers unique identification opportunities to study trust shocks.

Our analysis yields three key findings. First, exposure to academic misconduct evidently damages university-industry trust, leading to persistent declines in both firm-to-university patent citations and joint patent applications. These negative effects persist up to five years after exposure, consistent with the reputation stickiness documented by Levine (2021) and Boone and Uysal (2020).

Second, firms respond to trust shocks by pivoting toward inter-firm R&D alliances rather than seeking alternative academic partners or increasing internal R&D. This strategic change fundamentally alters innovation characteristics, resulting in lower basicness and stronger product orientation in firms' patents.

Third, trust shocks propagate through innovation networks to affect market responses. Venture capitalists (VCs) significantly reduce both the likelihood and magnitude of investments in firms previously associated with universities that involve misconduct, suggesting broader implications for resource allocation in innovation ecosystems.

Our paper makes several contributions to the literature. First, we advance incomplete contracting theory in innovation studies by examining how networks reconfigure when informal contracting mechanisms fail, departing from prior work that focuses primarily

[2] Over 10% of Chinese firms have established research partnerships with universities(Hsu et al., 2024), reflecting the crucial role of academic institutions in China's innovation ecosystem.

[3] Despite government efforts to increase basic research funding from 2.76% of R&D expenditure in 2002 to 6.03% in 2020, this remains significantly below the 15% benchmark of technologically advanced countries. Meanwhile, paper retraction rates have quadrupled since 2015, reaching 2,318 cases in 2021, nearly double the 2020 figure.

on trust's facilitative role (Nguyen, 2018; Xie et al., 2022). While Kondo et al. (2021) document the withdrawal of inventors from collaboration due to trust issues, we provide a novel firm-level perspective by examining how organizations respond strategically when they lose trust in inventors. This analysis enriches our understanding of corporate science engagement (Krieger et al., 2024) by revealing how trust shocks undermine firms' ability to build on academic research, while also illuminating how these shocks impede the commercialization of early-stage university innovations (Lerner et al., 2024).

Second, this is the first study to examine academic misconduct as a trust shock in innovation networks. Using this exogenous variation, we identify the causal effects of trust destruction on innovation, advancing beyond prior studies that rely on macrolevel correlations between national trust and economic outcomes (La Porta et al., 1997; Kondo et al., 2021; Xie et al., 2022). This approach enables us to address endogeneity concerns and track the dynamic impacts of trust changes. Our findings reveal that misconduct exposure significantly disrupts UIC, with firms reducing both patent citations and joint applications with affected universities. The adverse effects persist up to five years after exposure, consistent with the reputation stickiness theory of Levine (2021) and Boone and Uysal (2020).

Third, we document a novel mechanism in the strategic responses of firms to trust shocks. Although prior research shows that firms typically react to external shocks by increasing internal R&D (Bloom et al., 2016), adjusting innovation direction (Hombert and Matray, 2018), or reducing novelty (Krieger et al., 2022), we find that firms primarily pivot toward inter-firm R&D alliances rather than seeking alternative academic partners or expanding internal R&D. This strategic shift creates a fundamental trade-off between basic research capabilities and product orientation. Building on Hsu et al. (2024), who demonstrate that UIC promotes product innovation, we extend this literature by revealing systematic shifts in firms' innovation characteristics following the loss of academic partnerships. Specifically, we find that the transition to inter-firm collaboration substantially reduces firms' basic research capabilities. This finding highlights the irreplaceable role of university partnerships in the innovation strategy of firms and competitive advantage (Krieger et al., 2024).

Fourth, we extend the innovation financing literature by documenting how trust shocks reshape VC allocation through innovation networks. While prior studies examine how VC promotes innovation (Lerner, 2000) and how innovation cycles affect VC decisions (Nanda and Rhodes-Kropf, 2013), we reveal the dynamic propagation of trust shocks. Whereas Bottazzi et al. (2016) establish the predictive power of cross-country trust levels for VC investments, our analysis captures the dynamic transmission of trust shocks through innovation networks. Following Chemmanur et al. (2014) seminal work on VC types and innovation outcomes, we demonstrate how VCs systematically respond to trust shocks through investment decisions. Our findings complement the moral hazard framework (Loyola and Portilla, 2024) by identifying how trust shocks create additional contractual frictions in VC screening. In contrast to the examination of the response of corporate venture capital to the deterioration of internal innovation (Ma, 2020), we document how compromised trust leads VCs to reassess investment risks and reallocate resources. This trust-based mechanism provides new insights into the spillovers of the innovation ecosystem (Hochberg et al., 2007) and quantifies the economic costs of trust deterioration.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and develops our hypotheses. Section 3 describes our data sources and variable construction. Section 4 examines how academic misconduct affects university-firm trust relationships. Section 5 investigates firms' strategic adjustments to academic misconduct, analyzing changes in R&D partnerships and innovation characteristics. Section 6 explores market responses to academic misconduct through VC allocation decisions. Section 7 concludes.

2 Prior Literature and Hypothesis Development

2.1 Contract Theory and Innovation Networks

Innovation activities are characterized by high uncertainty and complexity, making innovation collaboration an inherently incomplete contracting problem (Aghion and Tirole, 1994; Francois and Roberts, 2003). In innovation activities, significant information asymmetries exist between principals (firms) and agents (universities/firms). This asymmetry manifests itself in two dimensions: ex ante difficulties in fully assessing partners' research capabilities and integrity levels (adverse selection) (Bolton and Dewatripont, 2004), and ex post challenges in monitoring research processes and verifying research quality (moral hazard) (Hart and Moore, 2008; Loyola and Portilla, 2024). These contractual challenges are particularly pronounced in innovation contexts, where substantial investment risks and information asymmetries complicate the specification of knowledge ownership, control rights, and profit sharing arrangements (Xie et al., 2022).

To address these contractual frictions, the literature identifies two key governance mechanisms. The first comprises formal mechanisms, including detailed contractual provisions, monitoring systems, and incentive designs (Williamson, 2007). However, due to the unique nature of innovation activities, these mechanisms often face high design and implementation costs while yielding limited effectiveness (Holmstrom, 1989; Manso, 2011). The second involves informal mechanisms, particularly trust. Extensive research demonstrates that trust plays an irreplaceable role in innovation networks by reducing negotiation costs, minimizing monitoring requirements, and facilitating knowledge sharing (Williamson, 1993; Carlin et al., 2009).

Trust plays an especially critical role in UIC due to fundamental differences in organizational attributes. First, regarding goal orientation, universities pursue knowledge breakthroughs and academic reputation through open research, while firms prioritize commercial value and proprietary development (Rosenberg and Nelson, 1994; Aghion et al., 2008). Second, in terms of incentive structures, academic researchers' career advancement is primarily dependent on peer review and scholarly publications, while corporate researchers' performance is closely tied to marketable results (Stern, 2004; Sauermann and Stephan, 2013). Third, in terms of behavioral norms, universities emphasize research verifiability and reproducibility, while firms are cautious about sharing commercially sensitive information and tacit knowledge (Cohen et al., 2002; Santoro and Saparito, 2003).

These systematic differences create contractual challenges in UIC: difficulties in designing unified evaluation criteria, balancing knowledge exposure with protection, and defining intellectual property rights (Xie et al., 2022). Consequently, UIC relies heavily on informal mechanisms, particularly trust, to maintain relationships. Trust compensates for formal contractual limitations by fostering shared expectations and facilitating mutual understanding (Bruneel et al., 2010). However, this trust-based governance equilibrium remains potentially unstable. When trust experiences severe shocks, existing contractual arrangements may fail, triggering significant adjustments in innovation networks (Poppo and Zenger, 2002).

2.2 Trust Shocks and Innovation Network Reconfiguration

Academic misconduct represents a severe trust shock as it directly challenges the credibility of scientific research. Drawing from contract theory, we posit that such shocks affect innovation networks through three mechanisms. First, they increase firms' difficulty in evaluating and verifying research quality, exacerbating information asymmetry. Second, they weaken the disciplinary role of reputation mechanisms (Kondo et al., 2021), increasing moral hazard. Third, they may trigger broader concerns about the integrity of the academic community, affecting institutional trust (Glaeser et al., 2000; Azoulay et al., 2017). These changes significantly increase the contractual costs of UIC, leading firms to reduce their reliance on university research. Therefore, we propose:

H1: The exposure of academic misconduct leads firms to reduce both their citations to university patents and the number of UIC patents.

When trust in university partnerships is damaged, firms face strategic choices in reconfiguring their innovation networks. We identify four potential strategies: (1) switching to other universities (university substitution), (2) maintaining existing relationships despite trust issues (status quo), (3) internalizing R&D activities (internalization), or (4) increasing collaboration with other firms (firm substitution).

University substitution, while seemingly viable, faces two major contractual challenges. First, the "stigma effect"(Karpoff et al., 2008) generates broad skepticism about academic research quality, increasing information asymmetry and search costs. Second, inherent differences in objectives and incentive structures between universities and firms maintain high contractual design and enforcement costs (Aghion et al., 2008).

Maintaining the status quo avoids partner switching costs, but significantly increases monitoring and enforcement costs due to trust deficiency. Contract theory predicts that when trust fails as an informal governance mechanism, firms need to invest more resources in designing and enforcing formal contracts, which could lower the marginal benefits of collaboration than its marginal costs (Poppo and Zenger, 2002).

Internalization, while avoiding external contractual frictions through unified ownership and control, presents three key challenges. First, establishing comprehensive internal R&D capabilities requires substantial investments in fixed assets, creating significant sunk costs due to asset specificity (Williamson, 2007). Second, internal R&D often faces diseconomies of scale, making it difficult for individual firms to maintain leadership across multiple technological domains (Patel and Pavitt, 1997). Finally, abandoning external collaboration means losing opportunities to acquire complementary knowledge and capabilities (Arora et al., 2001), a particularly significant opportunity cost in knowledge-intensive industries.

Firm substitution emerges as a favorable strategy. Contract theory emphasizes that contractual design and enforcement costs decrease significantly when the collaborating parties share similar organizational attributes and incentive structures (Holmstrom and Milgrom, 1994). Interfirm collaboration offers three advantages: reduced goal incongruence through shared commercial orientation, reduced information asymmetry through similar organizational structures, and effective reputational constraints through market mechanisms(Klein and Leffler, 1981; Kondo et al., 2021).

Comparing the relative contractual costs of these strategies, inter-firm collaboration emerges as the preferred response to trust crises due to its lower information costs, stronger incentive compatibility, and better contractual enforceability. Thus, we propose:

H2: Following exposure to academic misconduct, firms mainly replace damaged university-industry relationships by increasing inter-firm R&D alliances.

2.3 Contractual Relationship Changes and Innovation Characteristics

Changes in contractual forms often lead to changes in innovation characteristics. Theoretical evidence demonstrates that the allocation of intellectual property and control rights significantly influences R&D direction and characteristics (Aghion and Tirole, 1994). In UIC, contractual arrangements need to balance academic freedom with commercial orientation. Higher autonomy of research in universities and their independence from short-term market pressures facilitate basic innovation (Cohen et al., 2002; Lerner et al., 2024). This basic research orientation is further reinforced by universities' specialized human capital, research facilities, and academic reputation incentives.

In contrast, inter-firm collaborative contracts emphasize commercial objectives. As both parties face market constraints and performance evaluations(Lacetera, 2009), contractual incentive mechanisms drive R&D activities toward more market-oriented applications (Hsu et al., 2024). Recent empirical research provides systematic evidence supporting these theoretical predictions. Arora et al. (2018) find that firms' reduced investment in basic research often coincides with a shift from university-industry partnerships to inter-firm collaborations, reflecting how contractual structures shape innovation direction. Similarly, Hsu et al. (2024), in their systematic study of Chinese firms, demonstrate that reduced university collaboration leads to significant decreases in both basic research characteristics and exploratory innovation, confirming the role of academic-industry contracts in shaping firm innovation characteristics.

We expect the transition from university-industry to inter-firm collaboration to influence innovation characteristics through two mechanisms. First, reduced university collaboration limits firms' ability to access and absorb basic research knowledge. Second, increased inter-firm collaboration strengthens product-oriented incentive mechanisms. Based on this analysis, we propose:

H3a: The shift from university-industry to inter-firm collaboration leads to a decrease in the basic research orientation of firm innovation.

H3b: The shift from university-industry to inter-firm collaboration leads to an increase in the product orientation of firm innovation.

2.4 Trust Crisis Transmission and Market Response

Contract theory predicts that agency problems affect resource allocation through market mechanisms (Holmström, 1979). This transmission is particularly salient in innovation activities, where uncertainty and information asymmetry lead market participants to rely heavily on signals for project quality assessment. As sophisticated market participants, VCs evaluate not only the projects themselves but also the quality and verifiability of the broader innovation environment during their decision-making process (Bernstein et al., 2016). Through extensive due diligence, they scrutinize firms' R&D collaboration networks as a crucial evaluation dimension.

The exposure of academic misconduct can influence VCs' evaluation of companies through three primary channels. First, it raises doubts about the reliability of existing innovation outputs. Since the contributions of UICs are often difficult to disaggregate, academic misconduct by research partners exposes firms to reputational risks regarding their innovation quality. Second, it weakens firms' future innovation capabilities. As universities serve as crucial sources of basic research, their damaged reputation affects firms' ability to access high-quality research resources. Third, it significantly increases ongoing monitoring costs (Kaplan and Strömberg, 2004). VCs need allocate additional resources to verify firms' R&D activities, raising investment governance costs.

These effects are particularly pronounced for firms with close ties to the implicated universities due to significant reputation spillover effects in innovation networks. Hochberg et al. (2007) demonstrate that collaboration networks serve as channels for both knowledge flows and reputation transmission. When core partners' reputations are damaged, firms often face associated trust crises. Lerner and Nanda (2020) further argue that trust deficiency leads to increased information screening and monitoring costs, directly affecting VCs investment willingness. Specifically, VCs need rely more heavily on formal due diligence and continuous monitoring, increasing investment transaction costs.

Based on the above analysis, we expect the negative impact of academic misconduct exposure to transmit through innovation networks to affect firms' financing capabilities, manifesting in both the likelihood and scale of funding. Therefore, we propose:

H4: Firms with prior collaborative relationships with universities involved in misconduct experience adverse effects on both their probability of receiving VC investment and the investment scale.

3 Data

This section details our data sources and sample construction. Our study draws on a comprehensive dataset spanning from 2010 to 2021, integrating multiple data sources. Below, we describe our data collection process and the construction of key variables.

3.1 Data Sources

3.1.1 Academic Misconduct Exposure

We manually collect academic misconduct cases from 2015 to 2021 through the National Natural Science Foundation of China (NNSFC) Supervision Committee. After rigorous screening, we identify 134 cases with complete information. These cases contain detailed information including researchers' names, project approval numbers, application codes, and affiliated institutions, spanning six disciplines: information science, medical science, engineering and materials science, life science, earth science, and chemistry (see Appendix Table A.1). Notably, our analysis is constrained to the provincial level as the data before 2019 only contain provincial-level institutional information rather than specific institution name. The use of officially disclosed cases offers distinct advantages: these cases undergo rigorous official investigation and review processes, providing authoritative definitions of misconduct. Moreover, they typically involve severe penalties, such as research fund retraction and multi-year funding restrictions, suggesting more profound impacts on regional research environments and related industries.

3.1.2 Patent Information

We integrate patent data from three primary sources. From the China National Intellectual Property Administration (CNIPA) database, we obtain basic information for 18,647,651 patent applications filed in China during 2010-2021. This information includes patent application numbers, applicant information, patent abstracts, International Patent Classification (IPC) codes, application years, and addresses. Additionally, we collect citation data for each patent from the Google Patent database based on application numbers.

3.1.3 Venture Capital Data

We collect venture capital investment events in China from 2010 to 2021 using PEDATA. The data include information on investment institutions, target firms, firm addresses, industry classifications, investment dates, investment stages, currency types, and investment amounts. After excluding observations with missing location and timing information, our final sample contains 12,353 VC investments.

3.1.4 Additional Data

We incorporate several supplementary data sources. From the China City Statistical Yearbook, we collect detailed municipal economic data, including GDP per capita, GDP share of the secondary industry, fiscal budget expenditure, population size, number of higher education institutions and technology expenditure. These data provide crucial regional control variables. Additionally, we obtain detailed firm-level information from the CSMAR database, including financial data, corporate governance structures, and R&D investments for listed companies.

3.2 Data Construction and Variable Definition

We construct three distinct data structures to examine the multidimensional effects of academic misconduct exposure on firm innovation activities.

3.2.1 City-Industry-Year Level Measures

Our city-industry-year panel construction involves three main steps. First, we map patent IPC codes to four-digit industry codes from the Chinese Industry Classification System (GB/T4754-2017) using the IPC-Industry Concordance Table issued by CNIPA. This step enables precise industry identification for each patent. We also geocode patent applications to the city level using address information. Second, following Hall et al. (2001), we match the patent IPC codes with the six disciplines of the NNSFC. The discipline-IPC correspondence is detailed in the Appendix Table A.1. This matching allows us to link misconduct exposure data with patent data at the city-industry-year level. Retaining only city-industry combinations with patent applications during our sample period, we construct a panel dataset covering 800 industries across 218 cities from 2010 to 2021, totaling 526,092 observations.

Trust is a critical factor in fostering and maintaining university-industry partnerships, and misconduct can introduce uncertainty and erode the foundation of trust necessary for effective collaboration. Academic misconduct may generate uncertainty among industry partners and skepticism about the credibility of university research outputs and collaborations. At the city-industry-year level, we therefore employ two key indicators to reflect the interruption of trust caused by academic misconduct in universities: *Firm-to-University Patent Citations* and *University-Firm Collaborative Patents*.

To identify patent applicants, we establish classification criteria through textual analysis of applicant names. For public research institutions, we identify keywords such as university, college, research institute, academy and hospital. This keyword selection draws from systematic analysis of the naming conventions of Chinese research institutions. For firm patents, we identify profit-oriented entities through keywords such as company, factory, enterprise, and group. This classification method accounts for the organizational characteristics of the Chinese, ensuring accurate identification (Hsu et al., 2024).

For patent citations, we count firm to university citations at the city-industry-year level. Following Lerner and Seru (2022), we standardize citation counts within industries to account for cross-industry heterogeneity. For UIC, we identify co-patents with both firm and university applicants, aggregating counts at the city-industry-year level.

These two patent-based indicators reflect how academic misconduct can weaken trust in the credibility and reliability of research from affected universities. Patent citations reflect knowledge flows and recognition, while collaborative patents indicate deeper trust relationships requiring substantial resource commitment and risk-sharing. Notably, our choice of city-industry-year analysis aligns with the geographical proximity and industry relevance characteristics of UIC (Bikard and Marx, 2020; Hsu et al., 2024; Lerner et al., 2024).

Capturing Academic Misconduct Exposure at City-Industry Level. Academic misconduct exposure exhibits dual discipline-region characteristics, providing an ideal setting for causal identification using difference-in-differences methodology. We construct a treatment identifier, *Exposure*, at the city-industry-year level. This variable is equal to 1 for city-industry combinations affected by misconduct exposure in their corresponding discipline, and 0 otherwise. The *Post* variable equals 1 for years following exposure and 0 otherwise. Our key explanatory variable, $Exposure \times Post$, captures the causal effect of misconduct exposure by measuring the differential changes in outcome variables between the treatment and control groups before and after exposure.

This construction method accounts for both disciplinary and regional attributes of academic misconduct, enabling precise identification of affected research communities. Using NNSFC official misconduct case announcements as exogenous shocks, our approach provides a robust framework to estimate the causal effects of misconduct exposure.

3.2.2 Innovation Pair-Year Level Measures

We futher construct an Innovation Pair-Year panel dataset to examine how academic misconduct exposure affects firms' R&D collaboration networks. Our focus on listed companies ensures data availability and reliability while providing rich firm characteristics for mechanism analysis. The data construction process begins by matching listed companies from the CSMAR database to patent data through company names, yielding 2,045,853 patent applications by listed companies from 2010 to 2021. Among these, we identify 245,037 collaborative patent applications with multiple applicants, comprehensively covering listed companies' R&D collaborations with various innovation partners.

Following the patent classification criteria outlined in Section 3.2.1, we categorize innovation pairs into two types: firm-firm pairs and firm-university pairs. Firm-firm pairs consist of listed companies and other enterprises, identified through the co-occurrence of business entities in patent applications, totaling 36,447 pairs that reflect the dynamics of inter-firm R&D alliances. Firm-university pairs comprise listed companies and academic institutions, identified through co-occurrence of business and academic entities in patent applications, totaling 8,679 pairs that capture the evolution of industry-academia partnerships. This innovation pair structure enables a comprehensive analysis of how academic misconduct exposure affects firms' innovation networks, particularly revealing firms' strategic adjustments across different types of collaboration partners.

Measures of R&D Partnerships. We measure R&D partnership intensity using the number of collaborative patents at the innovation pair-year level. Specifically, we count patent applications for each innovation pair annually, categorizing them into firm-firm and firm-university collaborative patents. This approach allows us to examine the dynamic adjustments in both inter-firm and firm-university R&D relationships following misconduct exposure. Collaborative patents reflect substantive R&D cooperation, as joint patent applications typically involve extensive knowledge sharing and resource integration, representing deeper trust relationships than simple technology purchases or consulting arrangements. Moreover, collaborative patent output requires sustained prior investment and close coordination, effectively capturing long-term cooperation commitment between partners.

Capturing Academic Misconduct Exposure at Innovation Pair Level. We construct treatment identifiers separately for firm-firm and firm-university innovation pairs. For firm-university pairs, we define treatment groups as pairs where the university partner experiences misconduct exposure, with other firm-university pairs serving as controls. Specifically, we create a dummy variable *Exposure* that equals 1 if the university partner in an innovation pair experiences misconduct exposure during the sample period, and 0 otherwise.

For firm-firm pairs, our treatment identification considers whether either firm had prior patent collaboration with universities involved in misconduct. Specifically, we identify firm-firm pairs as treated if either firm had pre-existing collaboration with a university that experienced misconduct exposure in the relevant discipline. This approach enables us to trace the spillover effects of academic misconduct through firms' collaboration networks.

3.2.3 Firm-Year Level Measures

We construct two firm-level panel datasets to examine the impact of academic misconduct exposure: one focusing on listed companies to analyze changes in innovation characteristics, and another based on venture capital-backed firms to study changes in venture capital financing.

For the listed company sample, we begin with all A-share listed companies from 2010 to 2021 in the CSMAR database. We exclude firms without patent applications during the sample period, as well as financial firms (due to their distinct accounting standards and business models) and special treatment (ST) firms (due to financial distress potentially affecting innovation decisions) (Edmans et al., 2012). The final balanced panel consists of 1,097 listed companies with 13,164 firm-year observations.

Patent Basicness. Following Liu and Rosell (2013), we measure a patent's basicness through the breadth of its technological impact across fields. The basicness measure is calculated as:

$$Basic_k = \left(\sum_T \frac{Citation_T}{Citation_p}\right)\left(\frac{Citation_p}{Citation_p - 1}\right) \tag{1}$$

where p denotes the patent, T represents the technologies fields (defined by 4-digit IPC codes), $Citation_p$ is the total of citations received by the patent p, and $Citation_T$ is the number of citations from the technology field T. Higher values of $Basic_k$ indicate broader technological impact across multiple fields. We calculate this measure for each patent and then average across all patents filed by a firm in a given year.

Product Orientation. We construct a product orientation measure based on IPC classifications to capture firms' commercial development priorities. We first identify patents filed solely by firm itself to better reflect the intentions of autonomous product development (Hsu et al., 2024). We then classify the technology fields as product-oriented based on their 4-digit IPC codes, focusing on areas directly related to product development, such as agricultural machinery (A01D), medical devices (A61B), industrial processing equipment (B01D), mechanical power devices (F01B), measurement equipment (G01B), and electronic devices (H01H) (detailed in Appendix Table B.1). A patent is classified as product-oriented if it is filed independently by the firm and falls within these technological domains. The firm-level product orientation measure is the annual proportion of product-oriented patents among all patent applications.

Measures of Venture Capital Investment. For the VC-backed firm sample, we construct a balanced panel of 3,418 VC-backed firms with 41,016 firm-year observations using PEDATA. We develop two measures of VC investment. First, *VC Amount* represents the total annual venture capital investment received by a firm. For investments in US dollars, we convert to RMB using monthly average exchange rates at the time of investment. Second, *VC Dummy* is a binary variable equal to 1 if a firm receives any VC investment in a given year, and 0 otherwise.

Capturing Academic Misconduct Exposure at Firm Level. Our treatment identification strategy at the firm-year level builds on firms' collaboration networks. We define treatment groups as firms with patent collaborations with affected universities prior to misconduct exposure, while firms without such collaborations serve as controls. This approach captures the multiple shocks firms face when their university partners experience misconduct: the need to reevaluate existing partnerships and potentially adjust overall innovation strategy and resource allocation decisions.

3.2.4 Controls

We construct control variables at multiple levels to account for factors that can influence innovation activities. These controls fall into three categories: city characteristics, firm characteristics, and partnership features.

At the city level, we develop a set of controls that capture the regional innovation environment. We measure economic development using the natural logarithm of the gross domestic product (*GDP*) and industrial structure using the ratio of secondary industry to GDP (*Industrial Structure*). We also include measures of innovation resource endowment: the number of universities (*University*), local government science and technology expenditure (*S&T Expenditure*), and population density (*Population*). These variables capture regional educational resources, government innovation support, and human capital agglomeration.

For innovation pair analysis, we focus particularly on geographical proximity between innovation partners. We obtain precise geographical coordinates (latitude and longitude) through the Baidu Maps API and calculate the linear distance between collaborating entities based on these coordinates.

For firm characteristics, focusing on listed companies due to data availability, we control for several key dimensions. We measure industry concentration using the Herfindahl-Hirschman Index (*HHI*), R&D investment using the ratio of R&D expenditure to sales revenue (*R&D Intensity*), and government support through R&D subsidies (*R&D Subsidies*). For corporate governance characteristics, we include a state ownership dummy (*SOE*) and ownership concentration (*OWNCON*), measured as the sum of shareholdings of the top ten tradable shareholders.

3.3 Characteristics and Trends of Academic Misconduct Cases (2015-2021)

Using a comprehensive sample of 134 academic misconduct cases adjudicated by the NNSFC from 2015 to 2021, we document the systematic variation in the temporal, disciplinary and spatial distribution of enforcement actions.

The temporal distribution of academic misconduct exhibits a bimodal pattern over our sample period from 2015 to 2021. Following an initial 7.46% of cases in 2015, we document two distinct enforcement waves: the first during 2016-2017 (46.27% of total cases) and the second in 2021 (29.85%). The intervening period (2018-2020) saw significantly lower enforcement intensity, with cases declining to 16.42% of the sample. This cyclical pattern suggests an intensity of regulatory enforcement that varies over time, with potential deterrence effects following periods of increased scrutiny.

Figure 1 plots temporal trends in the disciplinary distribution and types of misconduct of 134 cases from 2015 to 2021. From a disciplinary perspective, Medical Science consistently accounts for the largest proportion of misconduct cases across years. The peak occurred in 2017 with 27 cases, followed by 2021 with 17 cases. Life Science and Engineering & Materials also show notable numbers, particularly in 2016-2017 and 2021, with about 5 cases each year.

Regarding types of misconduct, Publication Misconduct (including plagiarism, duplicate publication, and improper authorship) represents the most common violation. For example, in 2017, there were 28 cases of publication misconduct. Application Fraud (including providing false information in grant applications) shows the second highest frequency, with a significant spike in 2016 reaching 26 cases. Data Fabrication cases appear less frequently but remain consistent across years, typically 3-5 cases annually.

Figure 2 maps the geographical distribution of academic misconduct cases in China from 2015 to 2021. Spatially, these cases show significant regional clustering, predominantly in coastal regions, with Shanghai (28 cases), Jiangsu (16 cases), Liaoning (15 cases), and Beijing and Shandong (14 cases each) reporting the highest frequencies. By discipline, medical sciences (92 cases, 55.8%) and life sciences (42 cases, 25.5%) dominate

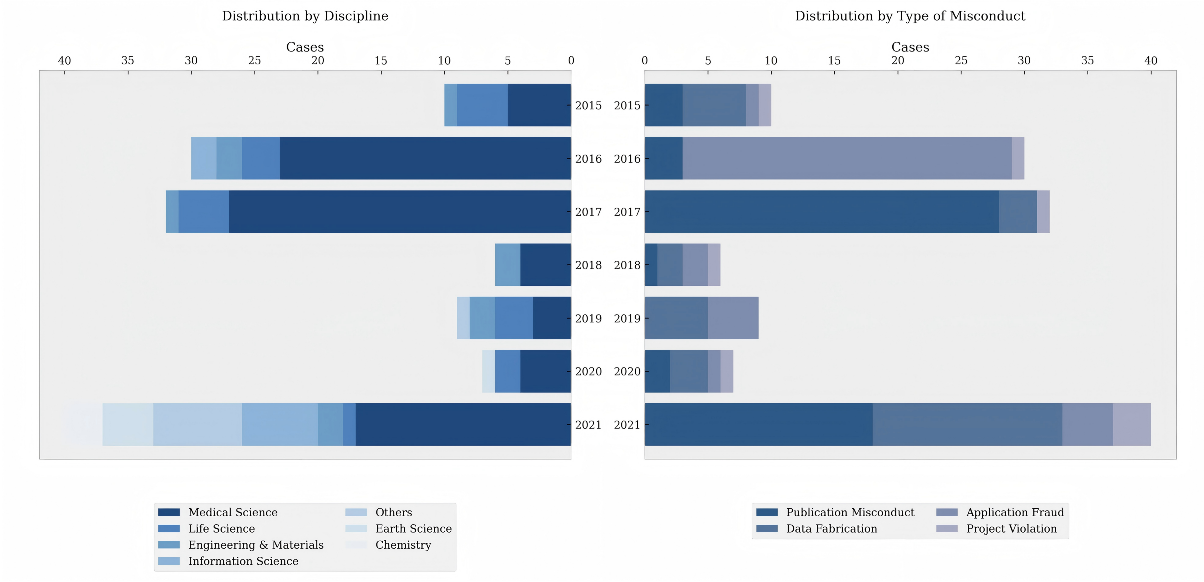


Figure 1: Analysis of Academic Misconduct Cases by Discipline and Type (2015-2021)

Notes: This figure illustrates the temporal and disciplinary distribution of 134 academic misconduct cases in China from 2015 to 2021, based on data from the National Natural Science Foundation of China Supervision Committee and the China Research Integrity website. The left panel shows the distribution by academic disciplines (Medical Science, Life Science, Engineering & Materials, Information Science, Earth Science, Chemistry, and Others), while the right panel displays the distribution by types of misconduct (Publication Misconduct, Data Fabrication, Application Fraud, and Project Violation). The horizontal bars represent the number of cases for each year, and different shades of blue are used to distinguish between disciplines and types of misconduct.

Figure 2: Geographical Distribution of Academic Misconduct Cases in China

Notes: This figure maps the spatial distribution and disciplinary classification of 134 academic misconduct cases in China from 2015 to 2021, based on data from the National Natural Science Foundation of China Supervision Committee and the China Research Integrity website. Different marker shapes denote distinct disciplines: squares for Engineering and Materials Science, triangles for Life Sciences, circles for Medical Sciences, hexagons for Chemical Sciences, diamonds for Information Sciences, stars for Earth Sciences, and dots for Other disciplines. Marker sizes are proportional to the number of disclosed cases in each region.

the distribution.

This geographical distribution pattern raises potential endogeneity concerns for staggered difference-in-differences (staggered DiD) estimation of the effects of academic oversight policies. First, regional clustering suggests that economically developed areas, typically hosting more universities and research institutions, may exhibit higher information transparency and regulatory capacity, potentially affecting observed case frequencies. Second, disciplinary imbalance indicates systematic differences across fields, possibly correlated with discipline-specific characteristics (e.g., experimental dependence, funding intensity).

To address these endogeneity concerns, our empirical design explicitly controls for regional heterogeneity through variables capturing local research capacity and economic development, including the number of universities, science and technology expenditure, and regional GDP. This approach helps mitigate estimation bias arising from regional heterogeneity.

3.4 Sample Descriptive Statistics

Table 1 presents descriptive statistics for our main variables. Key measures of *Firm-to-University Patent Citations*, *University-Firm Collaborative Patents*, *MisconductCopat*, and *NoMisconductCopat* exhibit strong right-skewed distributions. These variables show zero values at the 25th, 50th and 75th percentiles, while their means are significantly higher than medians. This pattern indicates that UIC is highly concentrated among a small number of firms, consistent with findings from Hsu et al. (2024) using Chinese patent data. This uneven distribution reflects not only significant heterogeneity in firms' ability to absorb and utilize university research resources, but also suggests the vulnerability of collaboration networks: When key universities face trust crises, negative impacts may disproportionately spread throughout the innovation network.

4 Academic Misconduct and University-Firm Trust

4.1 Model Specification

Academic misconduct exposures exhibit distinct disciplinary and geographical patterns, typically concentrating within specific fields and research institutions. This variation in discipline-region provides an ideal setting for identification. We employ a staggered DiD approach at the city-industry-year level to examine how misconduct exposure affects university-firm trust. Our baseline specification is:

$$Y_{c,j,t} = \alpha + \beta Exposure_{c,j} \times Post_t + \phi_{c,j,t} + Controls + FE_{c,j} + FE_t + \varepsilon_{c,j,t} \quad (2)$$

Table 1: Descriptive Statistics

	Obs.	Mean	SD	Min	P25	Med.	P75	Max
Panel A: City-Industry-Year Level Variables (2010-2021)								
City-Industry (N=43,841):								
Firm-to-University Patent Citations	526,092	0.235	0.751	0.000	0.000	0.000	0.000	18.660
University-Firm Collaborative Patents	526,092	0.078	0.422	0.000	0.000	0.000	0.000	20.016
City characteristics:								
GDP	526,092	10.666	0.502	8.576	10.284	10.690	11.067	12.073
University	526,092	2.640	1.111	0.000	1.792	2.398	3.738	4.489
Population	526,092	617.627	384.383	11.000	368.000	585.000	766.000	2,539.000
Industrial struct.	526,092	42.061	10.232	14.480	34.700	41.250	49.010	75.110
Government Size	526,092	0.128	0.053	0.045	0.095	0.118	0.147	1.485
S&T expend.	526,092	10.787	1.380	7.651	9.884	10.700	11.580	14.519
Admin Level	526,092	0.066	0.248	0.000	0.000	0.000	0.000	1.000
Panel B: Innovation Pair-Year Level Variables (2010-2021)								
Firm-University Pairs (N=8,679):								
CoPat	104,153	0.151	0.508	0.000	0.000	0.000	0.000	6.939
Distance	104,153	3.694	3.135	-6.807	0.000	3.912	6.895	8.046
Firm-Firm Pairs (N=36,447):								
CoPat	437,368	0.156	0.469	0.000	0.000	0.000	0.000	2.492
Distance	437,368	3.446	3.210	-9.681	0.000	3.287	6.825	8.251
Panel C: Firm-Year Level Variables (2010-2021)								
Listed Companies (N=1,097):								
MisconductCopat	13,164	0.073	0.344	0.000	0.000	0.000	0.000	2.312
NoMisconductCop.	13,164	0.198	0.603	0.000	0.000	0.000	0.000	3.260
SoloPatent	13,164	1.741	1.911	0.000	0.000	1.444	3.180	7.042
Patent Basic.	13,164	2.027	2.370	0.000	0.000	0.000	4.488	8.106
Share Product Pat.	8,692	0.290	0.329	0.000	0.000	0.167	0.500	1.000
Firm characteristics:								
HHI	13,164	0.198	0.236	0.000	0.041	0.123	0.211	1.000
R&D intensity	13,164	2.153	3.594	0.000	0.000	0.000	3.530	36.880
SOE	13,164	0.426	0.494	0.000	0.000	0.000	1.000	1.000
OWNCON	13,164	49.872	27.937	0.000	37.410	57.824	72.038	97.948
R&D Subsidies	13,164	8.466	7.305	0.000	0.000	12.899	15.014	20.235
VC-backed Firms (N=3,418):								
VCDummy	41,016	0.015	0.120	0.000	0.000	0.000	0.000	1.000
VCamount	41,016	0.062	0.552	0.000	0.000	0.000	0.000	8.816

Notes: This table presents descriptive statistics for our main variables. Panel A reports city-industry-year level variables. *Firm-to-University Patent Citations* measures firms' citations to university patents, standardized by industry-year. *University-Firm Collaborative Patents* captures the number of university-industry collaborative patents, similarly standardized. City characteristics include: *GDP* (natural logarithm), *University* (number of higher education institutions), *Population* (10,000 persons), *Industrial Structure* (secondary industry share of GDP, %), *Government Size* (fiscal expenditure to GDP ratio), *S&T Expenditures* (natural logarithm), and *Admin Level* (provincial capital dummy). Panel B presents innovation pair-year level variables. *CoPat* measures collaborative patent applications (IHS transformed). *Distance* captures geographical distance between partners (natural logarithm). Panel C reports firm-year level variables. For Listed Companies: *MisconductCopat* measures collaborative patents with universities involved in misconduct; *NoMisconductCopat* captures collaborative patents with universities not involved in misconduct; *SoloPatent* counts independently filed patents; *Patent Basicness* measures fundamental nature of patents; *Share of Product Patents* represents proportion of product-oriented patents. Firm characteristics include: *HHI* (Herfindahl-Hirschman Index), *R&D Intensity* (R&D to sales ratio), *SOE* (state-owned enterprise dummy), *OWNCON* (top 10 shareholders' holdings), and *R&D Subsidies* (natural logarithm). For VC-backed Firms: *VCDummy* indicates VC investment receipt; *VCamount* measures investment scale (IHS transformed). All continuous variables are winsorized at 1% and 99% percentiles.

where the dependent variable $Y_{c,j,t}$ represents two measures for city c, industry j, in year t: *Firm-to-University Patent Citations* and *University-Industry Collaborative Patents*. $Exposure_{c,j}$ is a dummy variable indicating whether a relevant discipline in a city-industry combination has experienced misconduct exposure. $Post_t$ equals one for years following the exposure. The coefficient β identifies the causal effect of misconduct exposure on university-firm trust by capturing the differential changes in outcome variables between treatment and control groups before and after exposure.

Following Fuest et al. (2018), we include time trends specific to the treatment group $\phi_{c,j,t}$ to control for potential differential dynamics. City-level controls include GDP, industrial structure, number of universities, science and technology expenditure, population size, and government size. Since misconduct events may affect regional characteristics (e.g., S&T expenditure), these time-varying controls could be outcomes of the shock, constituting bad controls (Cinelli et al., 2024; Angrist and Pischke, 2009). We address this by interacting baseline control variables with time trends to account for pre-shock differences between treatment and control groups. $FE_{c,j}$ and FE_t represent city-industry and year fixed effects, respectively. $\varepsilon_{c,j,t}$ is the error term. We use robust standard errors clustered at the city-industry level to address both temporal and cross-sectional correlation.

The validity of our staggered DiD approach relies on the parallel trends assumption, requiring similar trends in outcome variables between treatment and control groups absent intervention. To verify this assumption, we conduct an event study analysis:

$$Y_{c,j,t} = \alpha + \sum_{t=-4}^{-1} \mu_{-t} D_{c,j,t} + \sum_{t=1}^{6} \beta_t D_{c,j,t} + \phi_{c,j,t} + Controls + FE_{c,j} + FE_t + \varepsilon_{c,j,t} \tag{3}$$

Where $D_{c,j,t}$ represents the relative time dummies for the t period before and after misconduct exposure for city c and industry j. We omit the time dummy variable for the year before the occurrence of academic misconduct to avoid collinearity with fixed effects. Other variables remain consistent with Equation (2).

4.2 Results

Table 2 presents estimates from Equation (2). In columns (1)-(2), the dependent variable is *Firm-to-University Patent Citations* at the city-industry-year level. The coefficient on *Exposure*×*Post* in column (1) is -0.027 and significant at the 1% level. The effect remains significantly negative after including controls in column (2). Given the mean of *Firm-to-University Patent Citations* is 0.235 and standard deviation of 0.751, this estimate suggests that misconduct exposure reduces university patent citations by 8.63%.[4]

Columns (3)-(4) examine *University-Firm Collaborative Patents*. The *Exposure*×*Post*

[4] (-0.027×0.751)/0.235=-8.63%

coefficient of -0.008 in column (4) is significant. Given the mean of *University-Firm Collaborative Patents* is 0.078 and the standard deviation is 0.422, this implies a 4.33% [5] average decline in UIC patents for treated city-industry relative to controls. The similar magnitude of negative effects across both measures supports our key finding that academic misconduct exposure significantly damages university-firm trust.

Table 2: Academic Misconduct Exposure and University-Firm Trust

	Firm-to-University Patent Citations		*University-Firm Collaborative Patents*	
	(1)	(2)	(3)	(4)
Exposure×Post	-0.027***	-0.027***	-0.011***	-0.008**
	(0.005)	(0.005)	(0.004)	(0.004)
GDP		-0.000		-0.001***
		(0.001)		(0.000)
University		0.008***		0.003***
		(0.000)		(0.000)
Population		0.000*		0.000**
		(0.000)		(0.000)
Industrial structure		-0.000***		0.000***
		(0.000)		(0.000)
Government Size		0.018***		-0.000
		(0.004)		(0.002)
S&T expenditures		0.002***		0.002***
		(0.000)		(0.000)
Admin Level		-0.036***		0.013***
		(0.002)		(0.002)
Treatment time trends	YES	YES	YES	YES
City-Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Number of observations	526,092	526,092	526,092	526,092
Mean of Dependent Variable	0.235	0.235	0.078	0.078
S.D. of Dependent Variable	0.751	0.751	0.422	0.422

Notes: This table reports estimates of Equation (2) at the city-industry level. The dependent variables are *Firm-to-University Patent Citations* (columns 1-2) and *University-Firm Collaborative Patents* (columns 3-4), both standardized by industry-year. The coefficient on *Exposure×Post* measures the causal effect of academic misconduct exposure on university-firm trust, where *Exposure* indicates whether a city-industry's relevant discipline experienced misconduct exposure, and *Post* indicates years following exposure. Columns (2) and (4) include city-level controls (*GDP*, *University*, *Population*, *Industrial structure*, *Government Size*, *S&T expenditure*) interacted with time trends. All regressions include treatment group time trends, city-industry fixed effects, and year fixed effects. Standard errors clustered at city-industry level are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

These findings support *H1* that academic misconduct exposure leads firms to reduce both university patent citations and collaborative patenting. This can be explained through two theoretical lenses. First, from an information asymmetry perspective, misconduct exposure increases firms' difficulty in evaluating and verifying research quality (Bolton and Dewatripont, 2004), consistent with reduced university patent citations. Second, from a reputation deterioration perspective, this trust shock weakens academic

[5] $(-0.008 \times 0.422)/0.078$=-4.33%

reputation's disciplinary role (Kondo et al., 2021), increasing moral hazard and explaining reduced joint patent applications.

While these effects may appear modest at 4-8%, they represent economically significant impacts considering that our sample includes all city-industry combinations. The findings confirm that academic misconduct can trigger systemic trust crises in innovation networks (Azoulay et al., 2017), suggesting that firms can reevaluate and adjust their innovation collaboration strategies.

4.3 Subsample Regression and Robustness Check

Due to data availability, the NNSFC only released province-level misconduct data before 2019, with university-discipline level data available thereafter. This constrains our main analysis in equation (2) to province-level shocks, potentially weakening the causal link between regional misconduct and university-specific trust. For example, misconduct in Shanghai may not affect Fudan University's reputation, as elite institutions are often viewed independently of their regional context.

To address potential concerns about identification, we exploit detailed university-discipline level data in the post-2019 period. While data limitations preclude a conventional difference-in-differences design, we estimate the following specification using a university-industry-year panel:

$$Y_{i,j,t} = \alpha + \beta \mathit{Misconduct\_(1\text{-}3)Y}_{i,j,t} + \mathit{Controls} + FE_{i,j} + FE_t + \varepsilon_{i,j,t} \tag{4}$$

where i, j, and t index university, industry, and year. Following equation (4), the dependent variables are *Firm-to-University Patent Citations* and *University-Industry Collaborative Patents*. $\mathit{Misconduct\_(1\text{-}3)Y}_{i,j,t}$ equals 1 if the industry corresponding to the university's discipline experienced misconduct disclosure in the past one to three years, 0 otherwise. Controls include characteristics of cities where universities are located. We include university-industry and year fixed effects.

Table 3 presents university-industry level results. Consistent with baseline, academic misconduct reduces innovation collaboration. Collaborative patents decrease by 0.155 in the first year post-misconduct, with effects intensifying to -0.219 and -0.221 over two and three years. Firm citations to university patents similarly decline by 0.108 and 0.121 over two and three years.

An alternative explanation suggests that misconduct lowers the quality of university research, reducing firm collaboration. However, columns (7)-(9) show insignificant effects on university patent quality[6], indicating an unchanged research capability. The decline

[6]We measure university patent quality using Patent Knowledge Width. Patent Knowledge Width = $1-\sum \alpha^2$, where α represents the share of each IPC group classification. A higher value indicates a greater disparity between patent classifications at the group level, suggesting a wider breadth of knowledge across technological domains.

in collaboration probably reflects damaged trust rather than quality deterioration.

Table 3: University-Industry Level Analysis of Academic Misconduct Impact

	University-Firm Collaborative Patents			*Firm-to-University Patent Citations*			*University Patent Quality*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Misconduct_1Y	-0.155***			-0.068			0.010		
	(0.042)			(0.080)			(0.025)		
Misconduct_2Y		-0.219***			-0.108*			-0.002	
		(0.049)			(0.061)			(0.018)	
Misconduct_3Y			-0.221***			-0.121**			-0.003
			(0.050)			(0.059)			(0.017)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
University-Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	643,460	643,460	643,460	643,460	643,460	643,460	643,460	643,460	643,460
Mean of Dependent Variable	0.411	0.411	0.411	1.089	1.089	1.089	0.031	0.031	0.031
S.D. of Dependent Variable	0.784	0.784	0.784	1.097	1.097	1.097	0.116	0.116	0.116

Notes: This table reports estimates of Equation (4) at the university-industry level. The dependent variables are *University-Firm Collaborative Patents* (columns 1-3), *Firm-to-University Patent Citations* (columns 4-6), and *University Patent Quality* (columns 7-9), all standardized by industry-year. *Misconduct_1Y*, *Misconduct_1Y*, and *Misconduct_1Y* are dummy variables that equal 1 if the university experiences academic misconduct in its corresponding industry within one year, two years, and three years, respectively, and 0 otherwise. All regressions include city-level controls interacted with time trends. Standard errors clustered at university-industry level are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

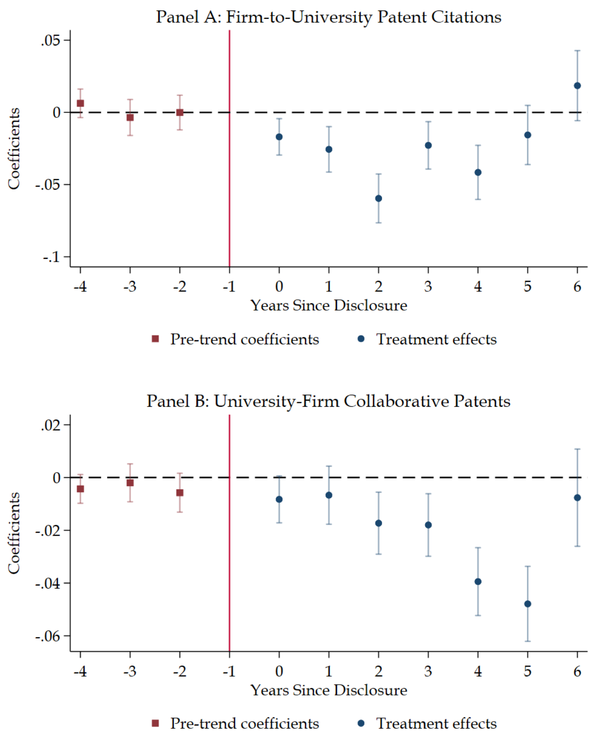


Figure 3: Academic Misconduct Exposure and University-Firm Trust

Notes: This figure presents event study estimates based on academic misconduct exposures from NNSFC, reporting coefficients μ_{-t} and β_t from Equation (3). Treatment groups are city-industry combinations experiencing misconduct, while control groups are unaffected city-industries. The year before Exposure serves as the reference period. Panel A shows the effect on firm-to-university patent citations; Panel B shows the effect on university-firm collaborative patents. Error bars represent 95% confidence intervals with standard errors clustered at city-industry level.

To validate our identification, we conduct an event study analysis. Figure 3 shows no significant pre-trends in either citation or collaboration measures, supporting the parallel trends assumption. Post-exposure, we document significant negative effects that persist through year five. The persistent negative impact on university-firm collaboration aligns with theories of reputation stickiness (Levine, 2021; Boone and Uysal, 2020), likely reflecting both the path dependence of innovation partnerships and systemic concerns about research integrity.

5 Firms Strategic Adjustments to Academic Misconduct

5.1 Changes in R&D Alliances

The results in section 4 demonstrate that academic misconduct exposure significantly and persistently damages university-firm trust relationships. Beyond reduced university patent citations and collaborative patenting, this trust deficit can trigger deeper adjustments in firms' R&D collaboration strategies. We examine how firms reconfigure their R&D alliance following academic misconduct shocks. Theoretically, firms may pursue four strategic adjustments: (1) firm substitution—shifting toward inter-firm R&D alliances as alternatives to university partnerships; (2) status quo maintenance—continuing collaborations with affected universities despite trust damage, due to resource dependence or sunk costs; (3) university substitution—redirecting partnerships toward universities without academic misconduct experience; or (4) internalization—strengthening independent R&D while reducing external collaboration dependence. We examine these strategic choices at both innovation-pair and firm levels.

To systematically analyze R&D alliance reconfiguration, we construct innovation pairs based on listed companies' collaborative patent data, employing the staggered DiD approach from section 4. Examining innovation at the pair level using collaborative patent counts offers a key advantage over firm-level analysis: it more precisely captures changes in bilateral cooperation intensity between firms and between firms-universities. To empirically test our hypotheses, we specify the following model:

$$CoPat_{i,j,t} = \alpha + \beta Exposure_{i,j} \times Post_t + \phi_{i,j,t} + Controls + FE_{i,j} + FE_t + \varepsilon_{i,j,t} \quad (5)$$

where $CoPat_{i,j,t}$ measures collaborative patent applications between entities i and j in year t, transformed using inverse hyperbolic sine (IHS) following Dyer et al. (2024). We categorize innovation pairs into firm-firm and university-firm pairs. For firm-firm pairs, treatment status depends on whether either firm had pre-existing patent collaboration with universities experiencing misconduct in relevant disciplines. For university-firm pairs, treatment indicates pairs where the university experienced misconduct exposure. $Exposure_{i,j}$ equals 1 for treatment pairs and 0 otherwise. $Post_t$ indicates years following misconduct exposure.

Similar to Equation (2), we control for treatment group time trends and city-level characteristics. Given prior evidence that geographical proximity significantly influences collaboration (Bikard and Marx, 2020; Hsu et al., 2024), we control for geographic distance between entities. We also include listed-firms characteristics: HHI, $R\&DIntensity$, SOE, $OWNCON$, and $R\&DSubsidies$. All controls enter as baseline values interacted with time trends. The model includes innovation pair fixed effects $FE_{i,j}$ and year fixed effects FE_t , with standard errors clustered at the innovation pair level.

While innovation pair analysis captures structural changes in R&D collaboration networks, it cannot fully test four strategic adjustments. For instance, pair-level data cannot effectively distinguish between university substitution and internalization strategies. We therefore complement our analysis with firm-level data, and specify the following model:

$$StrategyAdj_{i,t} = \alpha + \beta Exposure_i \times Post_t + \phi_{i,t} + Controls + FE_i + FE_t + \varepsilon_{i,t} \tag{6}$$

Where the dependent variable $StrategyAdj_{i,t}$ comprises three measures: *Misconduct-Copat*, representing the number of joint patents with misconduct-involved universities to assess status quo strategy; $NoMisconductCopat$, capturing the number of joint patents with universities not involved in misconduct to examine university substitution strategy; and $SoloPatent$, measuring the number of independently filed patents to evaluate internalization strategy. For treatment group identification, we classify firms with patent collaboration relationships with universities involved in misconduct prior to exposure to misconduct as the treatment group. Correspondingly, firms without such pre-exposure patent collaboration are assigned to the control group. Similar to the innovation pair-level model, our firm-level model controls for treatment group time trends, firm characteristics, and city-level attributes. The model includes firm and year fixed effects, with standard errors clustered at the firm level.

Table 4 presents innovation pair-level estimates. Panels A and B report effects on firm-firm and university-firm R&D alliances, respectively. Results reveal significant but opposite impacts. For firm-firm alliances (Panel A), treated pairs show a 5.2% increase in collaborative patents post-exposure. This supports the firm substitution strategy—firms seek alternative corporate partners when university trust erodes. For university-firm alliances (Panel B), treated pairs experience a 8.8% decrease in collaborative patents. This indicates that academic misconduct exposure significantly weakens university-firm R&D collaborations, confirming our findings about damaged university-firm trust from section 4.

These findings preliminarily support the prediction of $H2$ that firms substitute dam-

Table 4: Academic Misconduct Exposure and R&D Alliances

	Dependent variable: *CoPat*					
	Panel A: Firm-Firm R&D Alliances			Panel B: Firm-University R&D Alliances		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure×Post	0.050***	0.052***	0.052***	-0.088***	-0.085***	-0.088***
	(0.004)	(0.004)	(0.004)	(0.010)	(0.010)	(0.010)
Distance	-0.001***	-0.001***	-0.001***	0.014***	0.012***	0.010***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
HHI		-0.016***	-0.010***	-0.002***	-0.002***	-0.002***
		(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
R&D intensity		-0.000***	-0.000***		0.007***	0.006***
		(0.000)	(0.000)		(0.002)	(0.002)
SOE		0.003***	0.002***		-0.001***	-0.001***
		(0.001)	(0.001)		(0.000)	(0.000)
OWNCON		-0.000***	-0.000***		0.004***	0.003***
		(0.000)	(0.000)		(0.001)	(0.001)
R&D Subsidies		-0.000***	-0.000***		-0.000**	-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)
GDP			0.013***		-0.001***	-0.000***
			(0.001)		(0.000)	(0.000)
University			0.002***			0.005***
			(0.000)			(0.001)
Population			-0.000			0.002***
			(0.000)			(0.000)
Industrial structure			0.000***			-0.000***
			(0.000)			(0.000)
Government Size			0.043***			-0.000
			(0.011)			(0.000)
S&T expenditures			-0.007***			0.008**
			(0.000)			(0.004)
Admin Level			-0.002			-0.001
			(0.001)			(0.001)
Treatment time trends	YES	YES	YES	YES	YES	YES
Pair FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Number of observations	437,368	437,368	437,368	104,153	104,153	104,153
Mean of Dependent Variable	0.156	0.156	0.156	0.151	0.151	0.151
S.D. of Dependent Variable	0.469	0.469	0.469	0.508	0.508	0.508

Notes: This table reports estimates of Equation (5). The dependent variable *CoPat* measures the number of collaborative patent applications between innovation pairs (IHS transformed). Panel A presents results for firm-firm pairs, and Panel B for university-firm pairs. The coefficient on *Exposure×Post* measures the causal effect of academic misconduct Exposure on innovation collaboration. All specifications control for geographic distance between innovation partners (*Distance*). Columns (2) and (5) include firm-level controls: *HHI*, *R&D Intensity*, *SOE*, *OWNCON*, and *R&D Subsidies.* Columns (3) and (6) additionally control for city characteristics (*GDP*, *University*, *Population*, *Industrial structure*, *Government Size*, *S&T expenditure*, and *Admin Level*) interacted with time trends. All regressions include treatment group time trends, innovation pair fixed effects, and year fixed effects. Standard errors clustered at innovation pair level are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

aged university partnerships with increased inter-firm R&D alliances. The substantial substitution effect (5% increase in firm-firm collaboration versus 8% decrease in university-firm collaboration) aligns closely with contract theory predictions: contractual design and enforcement costs decrease significantly when partners share similar organizational attributes and incentive structures Holmstrom and Milgrom (1994). Firms demonstrate a preference for inter-firm collaboration over other potential substitution strategies.

However, innovation pair analysis has limitations. Primarily, pair data only capture realized collaborations, potentially missing comprehensive strategy shifts, particularly between university substitution and internalization. To overcome these limitations and conduct more comprehensive strategy testing, we supplement with firm-level panel analysis, examining adjustments along three dimensions: collaboration with affected universities (status quo), partnerships with unaffected universities (university substitution), and independent innovation (internalization).

Table 5 presents firm-level evidence further validating firms' strategic adjustments to academic misconduct exposure. Columns (1)-(2) show that misconduct exposure significantly reduces collaborative patents between firms and affected universities. After controlling for firm and regional characteristics, treated firms exhibit a 4.2% decrease in collaborative patents with affected universities relative to control firms. This result aligns with innovation pair-level findings, confirming misconduct exposure's detrimental effect on university-firm trust relationships.

Columns (3)-(4) examine firms' collaboration with unaffected universities. While negative, the coefficients are statistically insignificant, indicating that firms do not significantly increase collaboration with other universities. This suggests that university substitution is not firms' primary strategy, corroborating our innovation pair analysis and implying that misconduct shocks may trigger broader concerns about academic research quality. Columns (5)-(6) reveal that the coefficients for treated firms' independent patent applications are negative but statistically insignificant, indicating that firms do not pursue internalization strategies. Combined with innovation pair analysis, these results suggest firms prefer strengthening inter-firm collaboration to mitigate misconduct exposure's negative impacts.

These findings verify the core prediction in *H2*: facing trust shocks, firms favor the strategy with lowest contractual costs - increased inter-firm collaboration. This choice aligns with the organizational similarity principle, which suggests that contractual design and enforcement costs are minimized when partners share similar organizational attributes and incentive structures (Holmstrom and Milgrom, 1994). The finding also resonates with prior evidence that market mechanisms provide effective reputational constraints (Klein and Leffler, 1981).

Table 5: Academic Misconduct and Firms' Strategic Adjustments

	MisconductCopat		*NoMisconductCopat*		*SoloPatent*	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure×Post	-0.033*	-0.042**	-0.035	-0.040	-0.088	-0.082
	(0.019)	(0.020)	(0.030)	(0.030)	(0.084)	(0.083)
HHI	0.006	0.006	0.010	0.010	0.044*	0.046*
	(0.005)	(0.005)	(0.008)	(0.009)	(0.025)	(0.025)
R&D intensity	-0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)
SOE	0.006**	0.005**	0.012***	0.011**	-0.013	-0.007
	(0.002)	(0.002)	(0.004)	(0.004)	(0.012)	(0.013)
OWNCON	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D Subsidies	-0.000	-0.000	-0.000	-0.000	-0.002*	-0.002*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
GDP		0.006		0.011***		0.002
		(0.004)		(0.004)		(0.013)
University		0.003**		0.002		-0.006
		(0.001)		(0.002)		(0.007)
Population		-0.000*		-0.000		-0.000
		(0.000)		(0.000)		(0.000)
Industrial structure		-0.001***		-0.000		-0.001
		(0.000)		(0.000)		(0.001)
Government Size		0.077		0.020		-0.133
		(0.050)		(0.026)		(0.114)
S&T expenditures		-0.001		-0.003		0.007
		(0.002)		(0.002)		(0.007)
Treatment time trends	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Number of observations	13,164	12,996	13,164	12,996	13,164	12,996
Mean of Dependent Variable	0.073	0.073	0.198	0.198	1.741	1.741
S.D. of Dependent Variable	0.344	0.344	0.344	0.344	1.911	1.911

Notes: This table reports estimates of Equation (6). The dependent variables are: *MisconductCopat* (collaborative patents with misconduct-affected universities, testing status quo strategy, columns 1-2), *NoMisconductCopat* (collaborative patents with unaffected universities, testing university substitution, columns 3-4), and *SoloPatent* (independent patents, testing internalization, columns 5-6), all IHS transformed. The coefficient on *Exposure×Post* measures the causal effect of misconduct Exposure on firms' innovation strategies. Treatment firms are those with pre-Exposure patent collaborations with affected universities. Columns (1), (3), and (5) include firm-level controls: *HHI*, *R&D Intensity*, *SOE*, *OWNCON*, and *R&D Subsidies*. Columns (2), (4), and (6) additionally control for city-level controls (*GDP*, *University*, *Population*, *Industrial structure*, *Government Size*, *S&T expenditure*) interacted with time trends. All regressions include treatment group time trends, firm fixed effects, and year fixed effects. Standard errors clustered at firm level are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

5.2 Changes in Innovation Characteristics

Our empirical results suggest that firms respond to academic misconduct exposure by favoring inter-firm substitution strategy, reducing university collaboration in favor of strengthening R&D alliances with other firms. This transformation in innovation collaboration patterns likely induces significant changes in firms' innovation characteristics. Given the fundamental differences between university-industry and inter-firm collaborations, we expect this shift to affect both the basicness and product orientation of innovation.

Regarding innovation basicness, universities, as the main practitioners of basic research, typically focus on exploring scientific frontiers and fundamental principles. UIC provides firms with crucial channels to access and absorb basic knowledge (Cohen et al., 2002). The deep theoretical foundations, expertise, and advanced experimental facilities of university researchers enable firms to conduct more forward-looking research (Krieger et al., 2024; Lerner et al., 2024). Consequently, reduced university collaboration may weaken the basic research attributes of firms' innovation activities.

In contrast, increased inter-firm collaboration likely strengthens innovation's product orientation. As market entities, firms' R&D decisions are primarily driven by market demand and commercial returns. Inter-firm collaboration typically builds on complementary advantages and resource sharing, with partners focusing on converting their respective market and technological strengths into commercial value. Compared to UIC's longer R&D cycles and stronger exploratory nature, inter-firm collaboration usually sets more explicit commercial objectives and shorter investment recovery periods. Additionally, market competition pressures drive collaborating parties to emphasize innovation's application value and commercialization process.

Based on this analysis, we expect the shift in innovation collaboration patterns triggered by academic misconduct exposure to induce two changes in innovation characteristics: first, a decline in innovation basicness, potentially reflected in reduced basic research-related patents; second, enhanced product orientation, manifested in more product-oriented patents and stronger commercialization features. To examine how changes in collaboration patterns affect patent characteristics, we first construct the following staggered DiD model:

$$PatentChar_{i,t} = \alpha + \beta Exposure_i \times Post_t + \phi_{i,t} + Controls + FE_i + FE_t + \varepsilon_{i,t} \tag{7}$$

where $PatentChar_{i,t}$ includes two dimensions: *Patent Basicness* and *Share of Product-Oriented Patents*. $Exposure_i$ indicates firms with university collaboration prior to exposure and $Post_t$ denotes post-exposure periods. To identify mechanisms driving innovation characteristic changes, we introduce a triple-difference (DDD) specification with a *declined university collaboration* (DUC) dummy:

$$PatentChar_{i,t} = \alpha + \beta Exposure_i \times Post_t \times DUC + \phi_{i,t} + Controls + FE_i + FE_t + \varepsilon_{i,t} \quad (8)$$

where DUC equals 1 for firms experiencing reduced university collaboration post-exposure. This specification allows us to isolate characteristic changes specifically for firms that reduced university collaboration. The coefficient β captures differential changes in patent basicness and product orientation for treated firms reducing university collaboration.

Table 6 reports how misconduct exposure affects patent basicness and product orientation. The results provide systematic evidence linking collaboration pattern shifts to patent characteristics.

Table 6: Academic Misconduct and Changes in Patent Characteristics

	Patent Basicness				Share of Product-Oriented Patents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure×Post	-0.326***	-0.326***			0.005	0.006		
	(0.104)	(0.105)			(0.012)	(0.012)		
Exposure×Post×DUC			-0.675***	-0.733***			0.064***	0.070***
			(0.143)	(0.144)			(0.020)	(0.020)
HHI	0.016	0.017	0.017	0.017	0.002	0.003	0.003	0.004
	(0.033)	(0.033)	(0.033)	(0.033)	(0.005)	(0.005)	(0.005)	(0.005)
R&D intensity	-0.003	-0.004	-0.003	-0.004	-0.001***	-0.001**	-0.001***	-0.001**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
SOE	-0.018	-0.020	-0.020	-0.022	0.002	0.002	0.003	0.003
	(0.015)	(0.016)	(0.015)	(0.016)	(0.002)	(0.002)	(0.002)	(0.002)
OWNCON	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D Subsidies	-0.004***	-0.003***	-0.004***	-0.004***	-0.000*	-0.000*	-0.000*	-0.000*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
GDP		0.032		0.031		0.003*		0.003
		(0.024)		(0.023)		(0.002)		(0.002)
University		0.004		0.005		-0.002		-0.002
		(0.009)		(0.009)		(0.001)		(0.001)
Population		0.000*		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Industrial structure		0.000		0.000		0.000		0.000
		(0.001)		(0.001)		(0.000)		(0.000)
Government Size		0.041		0.043		-0.000		-0.002
		(0.181)		(0.172)		(0.018)		(0.018)
S&T expenditures		-0.010		-0.008		-0.002*		-0.003*
		(0.010)		(0.010)		(0.001)		(0.001)
Treatment time trends	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	13,164	12,996	13,164	12,996	8,635	8,537	8,635	8,537
Mean of Dependent Variable	2.027	2.027	2.027	2.027	0.290	0.290	0.290	0.290
S.D. of Dependent Variable	2.370	2.370	2.370	2.370	0.329	0.329	0.329	0.329

Notes: This table reports firm-level patent characteristic estimates based on equations (7) and (8). Columns (1)-(2) and (5)-(6) present estimates of equation (6), where the dependent variables are *Patent Basicness* (columns 1-2) and *Share of Product-Oriented Patents* (columns 5-6), respectively. The coefficient on *Exposure×Post* measures the causal effect of academic misconduct exposure on patent characteristics, where firms with patent collaboration relationships with misconduct-involved universities prior to exposure are identified as the treatment group. Columns (3)-(4) and (7)-(8) present estimates of equation (7). The triple interaction term *Exposure×Post×DUC* captures the differential changes in patent characteristics for treated firms that reduce university collaboration (DUC=1) following misconduct exposure, where DUC is a dummy variable equal to 1 if a firm experiences a decrease in university collaboration patents post-exposure. Columns (1), (3), (5), and (7) control for firm-level characteristics, including *HHI*, *R&D Intensity*, *SOE*, *OWNCON*, and *R&D Subsidies*. Columns (2), (4), (6), and (8) additionally include city-level controls (*GDP*, *University*, *Population*, *Industrial structure*, *Government Size*, *S&T expenditure*) interacted with time trends. All regressions control for treatment group time trends, firm fixed effects, and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

For patent basicness, misconduct exposure significantly reduces the fundamental research attributes of treated firms' patents. Post-exposure, treated firms' patent basicness decreases by 0.326 relative to control firms, representing 16.08% of the sample mean. Triple-difference estimates reveal stronger negative effects for firms reducing university collaboration, suggesting that reduced university partnerships indeed weaken firms' basic research capabilities, narrowing their patents' technological spillover scope.

Regarding product orientation, while exposure alone does not significantly affect the share of product-oriented patents, firms reducing university collaboration show a significant 7 percentage point increase. This indicates that firms shifting from university to inter-firm collaboration develop more market-oriented innovations focused on commercial products and equipment.

These findings systematically support *H3a* and *H3b*. First, the transition from university to firm collaboration significantly reduces patent basicness, validating the argument by Cohen et al. (2002) that universities' unique research autonomy and long-term orientation play irreplaceable roles in fundamental innovation.

Second, firms reducing university collaboration significantly increase their share of product-oriented patents, supporting *H3b*. This shift aligns with recent evidence that inter-firm collaboration, driven by shared market pressures and performance evaluations, steers innovation towards more applied directions(Hsu et al., 2024). This characteristic adjustment not only reflects how contractual structures shape innovation direction(Aghion and Tirole, 1994) but also reveals potential long-term innovation capability risks from substituting university partnerships.

5.3 Subsample Regression and Robustness Check

Similar to equation (4), we also perform subsample testing at the pair level. Table 7 presents the robustness tests using university-discipline level misconduct data. For firm-firm pairs (Panel A), firms experiencing misconduct disclosure increased their firm-firm innovation collaboration by 4.9%-6.4%. For university-firm pairs (Panel B), university-discipline level misconduct significantly reduced collaborative innovation, with negative effects intensifying from -9.3% in year one to -21% in year three. These findings using granular data validate our province-level shock results and mitigate concerns about regional-level misconduct inadequately capturing university-specific trust shocks.

We analyze the dynamic effects on firms' innovation collaboration (Figure 4) and patent characteristics (Figure 5) using event study methodology. The figures plot point estimates and their 95% confidence intervals across event time. With the exception of panel A1 in (Figure 4), coefficients in pre-exposure periods are statistically indistinguishable from zero across all panels. In panel A1, while the coefficient at t=-2 is insignificant, the coefficient at t=-4 is significantly negative. Despite this, the overall temporal pat-

Table 7: Academic Misconduct and R&D Alliances: Subsample Evidence

	Panel A: Firm-Firm R&D Alliances			Panel B: Firm-University R&D Alliances		
	(1)	(2)	(3)	(4)	(5)	(6)
Misconduct_1Y	0.049***			-0.093***		
	(0.011)			(0.018)		
Misconduct_2Y		0.064***			-0.114***	
		(0.009)			(0.015)	
Misconduct_3Y			0.054***			-0.210***
			(0.008)			(0.015)
Controls	YES	YES	YES	YES	YES	YES
Pair FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Number of observations	437,368	437,368	437,368	104,153	104,153	104,153
Mean of Dependent Variable	0.156	0.156	0.156	0.151	0.151	0.151
S.D. of Dependent Variable	0.469	0.469	0.469	0.508	0.508	0.508

Notes: This table reports regression results using university-discipline level subsample of academic misconduct shocks. The dependent variable *CoPat* measures the number of collaborative patent applications between innovation pairs (IHS transformed). Panel A presents results for firm-firm pairs, and Panel B for university-firm pairs. The coefficient on *Misconduct_1Y* indicates whether either partner in the pair experienced academic misconduct at the university level within one year, while *Misconduct_2Y* and *Misconduct_3Y* capture misconduct occurrences within two and three years respectively (all are dummy variables equal to 1 if misconduct occurred, 0 otherwise). All specifications control for *Distance*, *HHI*, *R&D Intensity*, *SOE*, *OWNCON*, *R&D Subsidies*, *GDP*, *Universities*, *Population*, *Industrial Structure*, *Government Size* and *S&T Expenditure*. Each control variable is interacted with time trends using its baseline value. All regressions include pair fixed effects and year fixed effects. Standard errors clustered at pair level are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

tern demonstrates largely similar trends between treatment and control groups prior to misconduct exposure, providing general support for the parallel trends assumption and validating our causal inference.

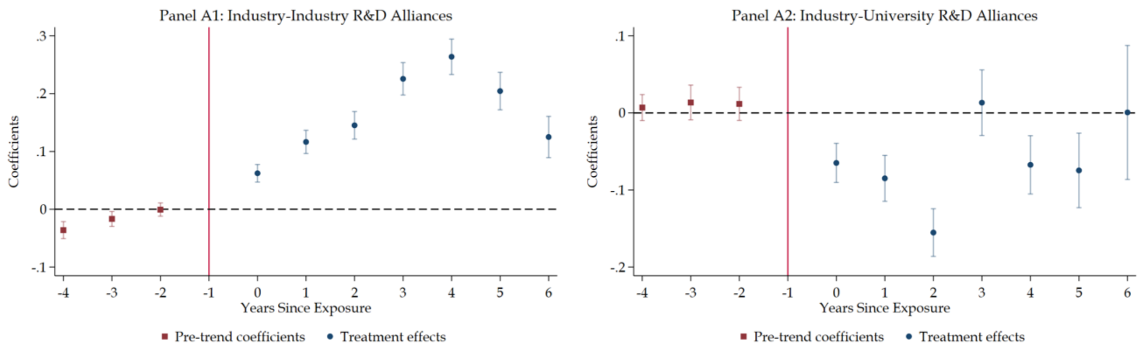
6 Market Response to Academic Misconduct

6.1 Model Specification

Our previous analysis demonstrates that exposure to academic misconduct damages firms' trust in universities, triggering adjustments in R&D collaboration patterns and innovation characteristics. However, this trust crisis extends beyond direct university-firm relationships, potentially transmitting through innovation networks to capital markets. When universities engage in academic misconduct, market investors can develop multiple concerns about their corporate partners: first, close collaboration with institutions affected by misconduct can question the reliability of firms' innovation outputs; second, reputational damage from partners can weaken firms' future innovation capabilities and market competitiveness; third, firms may incur substantial switching costs in seeking new R&D partners. This trust crisis spillover effect reflects a multilevel transmission chain: from the academic integrity crisis to university-firm trust breakdown, ultimately evolving into capital market distrust of affected firms.

VC investment decisions provide an ideal setting to examine this trust transmission mechanism. First, as sophisticated market investors, VCs conduct thorough due diligence, accurately identifying firms' R&D collaboration networks (Chemmanur et al.,

Panel A. Pair-level



Panel B. Firm-level

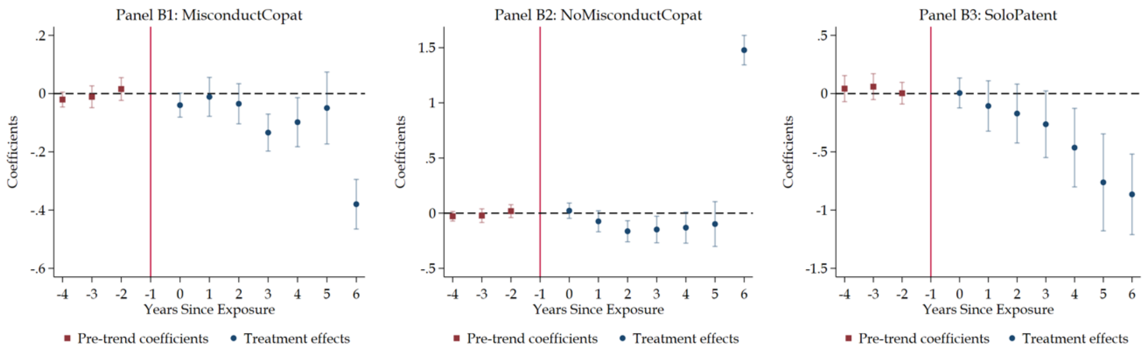


Figure 4: Academic Misconduct Exposure and Innovation Networks

Notes: This figure plots event study estimates of how academic misconduct exposure affect firms' innovation strategies, based on Equation (3). Panel A examines innovation network effects at the pair level. A1 shows firm-firm pairs where treatment is defined by either firm's pre-exposure collaboration with misconduct-involved universities. A2 shows university-firm pairs where treatment universities experienced misconduct. Panel B examines firm-level responses: changes in collaborations with misconduct-involved universities (B1, *MisconductCopat*), with other universities (B2, *NoMisconductCopat*), and in independent patenting (B3, *SoloPatent*). Treatment firms are those with pre-exposure ties to misconduct-involved universities. Red squares and blue circles indicate pre-trends and post-exposure effects, respectively. Bars show 95% confidence intervals with standard errors clustered at pair/firm level.

2014; Bernstein et al., 2016). Second, VCs are particularly sensitive to the innovation capabilities and growth prospects of firms (Tian et al., 2016), naturally responding to the reputational changes in firms' R&D partners. Third, compared to other market participants, VCs possess expertise in evaluating and managing innovation risks, making their investment decisions more precise indicators of market reactions to academic misconduct. Based on these considerations, we examine whether misconduct exposure affects firms' access to and scale of venture capital. If markets indeed develop trust concerns about firms collaborating with misconduct-involved universities, we expect these firms to face greater difficulties in securing venture capital.

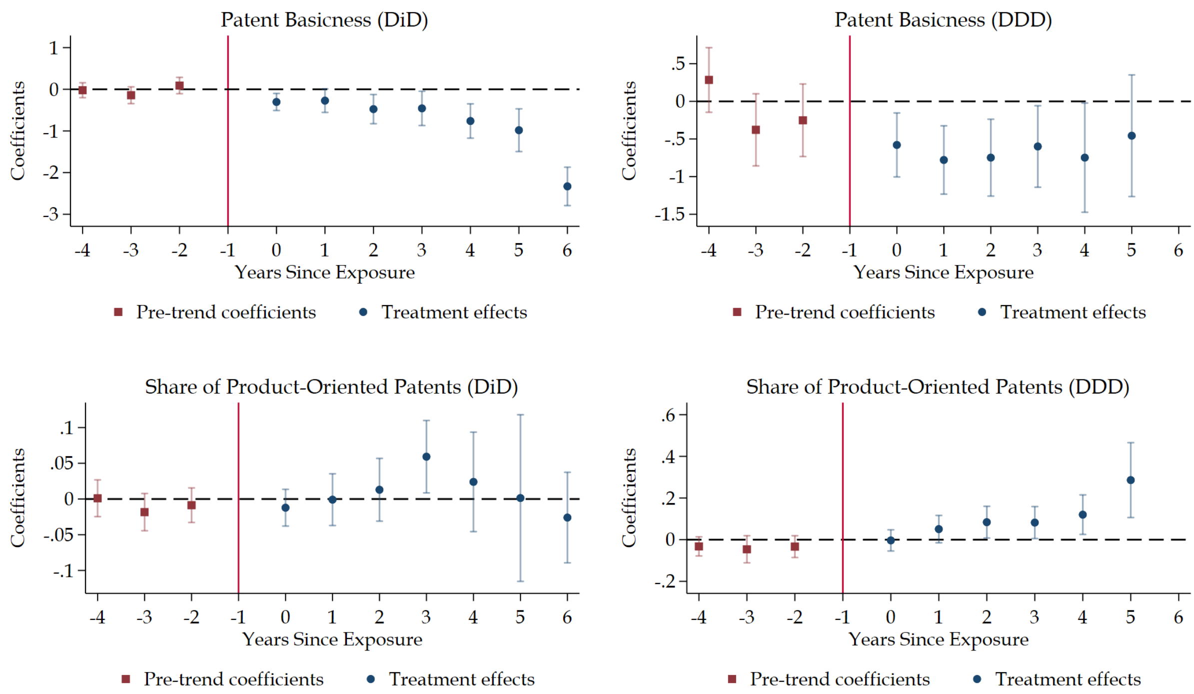


Figure 5: Academic Misconduct Exposure and Patent Characteristics

Notes: This figure presents event study results of academic misconduct exposure's effects on firm patent characteristics in China from 2010 to 2021. Panel A shows the dynamic changes in Patent Basicness. Panel A1 reports results under a DiD specification, while Panel A2 presents DDD estimates incorporating a university collaboration decrease dummy (DUC) to identify firms that actually reduced university collaboration post-exposure. Panel B displays the dynamic changes in Share of Product-Oriented Patents. Similarly, Panel B1 reports DiD results, while Panel B2 presents DDD estimates. Across all analyses, firms with pre-exposure patent collaboration relationships with misconduct-involved universities are identified as the treatment group. Red squares represent pre-exposure time trends between treatment and control groups, while solid blue circles represent treatment effects post-exposure. Bars indicate 95% confidence intervals with standard errors clustered at the firm level.

To examine how misconduct exposure affects VC acquisition, we specify:

$$VC_{i,t} = \alpha + \beta Exposure_i \times Post_t + \phi_{i,t} + Controls + FE_i + FE_t + \varepsilon_{i,t} \tag{9}$$

where dependent variables $VC_{i,t}$ include $VCdummy$ (indicating whether firm i receives venture capital in year t) and $VCamount$ (IHS-transformed). Due to data availability constraints, we only control for city-level characteristics. Other specifications follow Equation (7).To further identify VCs responses to firms' R&D collaboration adjustments, we estimate:

$$VC_{i,t} = \alpha + \beta Exposure_i \times Post_t \times DUC + \phi_{i,t} + Controls + FE_i + FE_t + \varepsilon_{i,t} \tag{10}$$

where DUC equals 1 for firms that reduce university collaboration after exposure.

This specification allows us to examine whether VCs respond differentially to firms' strategic adjustments. For firms reducing university collaboration, VCs may evaluate from two perspectives: first, such adjustment may signal proactive innovation risk management; second, as our previous analysis shows, these firms experience decreased patent basicness but increased product orientation, potentially influencing VC investment decisions.

6.2 Results

Table 8 reports how academic misconduct exposure affects firms' access to VC funding. Columns (1)-(4) examine the probability of receiving VC. The coefficient on *Exposure*$\times$*Post* is -0.012 and statistically significant, indicating that treated firms experience a 1.2 percentage point decrease in the probability of receiving VC relative to control firms. Given the sample mean of 0.015, this effect is economically substantial, representing a 80% reduction in venture capital access. The coefficient on *Exposure*$\times$*Post*$\times$*DUC* is -0.019 and significant at the 1% level, suggesting that VCs respond more strongly to changes in firms' R&D collaboration strategies. For firms reducing university collaboration after exposure, the probability of receiving VC decreases by 1.9 percentage points.

Similarly, we find that treated firms experience a 5.3% reduction in VC investment amounts relative to control firms post-exposure. This result indicates that VCs make substantial adjustments in response to misconduct exposure, reducing both their willingness to invest and investment scale. The triple-difference estimates reveal even stronger effects for firms reducing university collaboration, with a 9.3% decrease in investment amounts. These findings demonstrate that VCs make material adjustments in both investment probability and scale.

These results support *H4*, revealing how trust crises affect resource allocation through market mechanisms. First, the significant decline in VC access for firms with prior collaboration with affected universities aligns with previous findings that VCs heavily weight innovation environment quality and credibility (Bernstein et al., 2016). The stronger negative effects for firms reducing university collaboration confirm significant reputation spillover effects in innovation networks (Hochberg et al., 2007). Second, the substantial decrease in investment scale supports theoretical predictions that VCs adjust investment levels to address increased transaction costs from elevated information screening and monitoring requirements Kaplan and Strömberg (2004). This systematic market response not only validates the literature on how trust deficits affect VC decision-making Lerner (2000) but also reveals how academic misconduct, by undermining innovation network trust, may have broader resource allocation consequences.

Table 8: Academic Misconduct Exposure and Venture Capital Investment

	VCdummy				*VCamount*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Exposure \times Post$	-0.013***	-0.012***			-0.058***	-0.053***		
	(0.004)	(0.004)			(0.020)	(0.020)		
$Exposure \times Post \times DUC$			-0.018***	-0.019***			-0.091***	-0.093***
			(0.004)	(0.004)			(0.017)	(0.017)
GDP		0.000		0.000		0.001		0.001
		(0.000)		(0.000)		(0.002)		(0.002)
University		-0.000		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.001)		(0.001)
Population		-0.000		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Industrial structure		-0.000*		-0.000**		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Government Size		-0.001		-0.001		-0.006		-0.006
		(0.001)		(0.001)		(0.006)		(0.006)
S&T expenditures		0.000		0.000		0.001		0.002
		(0.000)		(0.000)		(0.001)		(0.001)
Treatment time trends	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	41,016	41,016	41,016	41,016	41,016	41,016	41,016	41,016
Mean of Dependent Variable	0.015	0.015	0.015	0.015	0.062	0.062	0.062	0.062
S.D. of Dependent Variable	0.120	0.120	0.120	0.120	0.552	0.552	0.552	0.552

Notes: This table reports firm-level estimates from equations (9) and (10). The dependent variables are a dummy variable indicating venture capital investment (*VCdummy*) in columns (1)-(4) and the IHS-transformed amount of venture capital investment (*VCamount*) in columns (5)-(8). Columns (1)-(2) and (5)-(6) present estimates from equation (8), where the coefficient on $Exposure \times Post$ measures the effect of academic misconduct exposure on venture capital investment. Columns (3)-(4) and (7)-(8) present estimates from equation (9), where the triple interaction term $Exposure \times Post \times DUC$ captures the differential changes in venture capital investment for treated firms that reduce university collaboration (DUC=1) following misconduct exposure. In all analyses, firms with pre-exposure patent collaboration relationships with misconduct-involved universities are identified as the treatment group. Columns (2), (4), (6), and (8) include city-level controls: *GDP*, *University*, *Population*, *Industrial structure*, *Government Size*, *S&T expenditure*. Each control variable is interacted with time trends using its baseline value. All regressions control for treatment group time trends, firm fixed effects, and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

6.3 Robustness

Figure 6 presents event study estimates of academic misconduct exposure's impact on venture capital funding using both DiD and DDD specifications. The plots show point estimates and their 95% confidence intervals across event time. In pre-exposure periods (marked by red squares), coefficients are statistically indistinguishable from zero across all panels, with confidence intervals consistently containing zero. This pattern holds for both the probability of receiving VC (Panels A1 and A2) and investment amounts (Panels B1 and B2), demonstrating similar pre-trends between treatment and control groups. These results provide robust support for the parallel trends assumption, validating our causal inference.

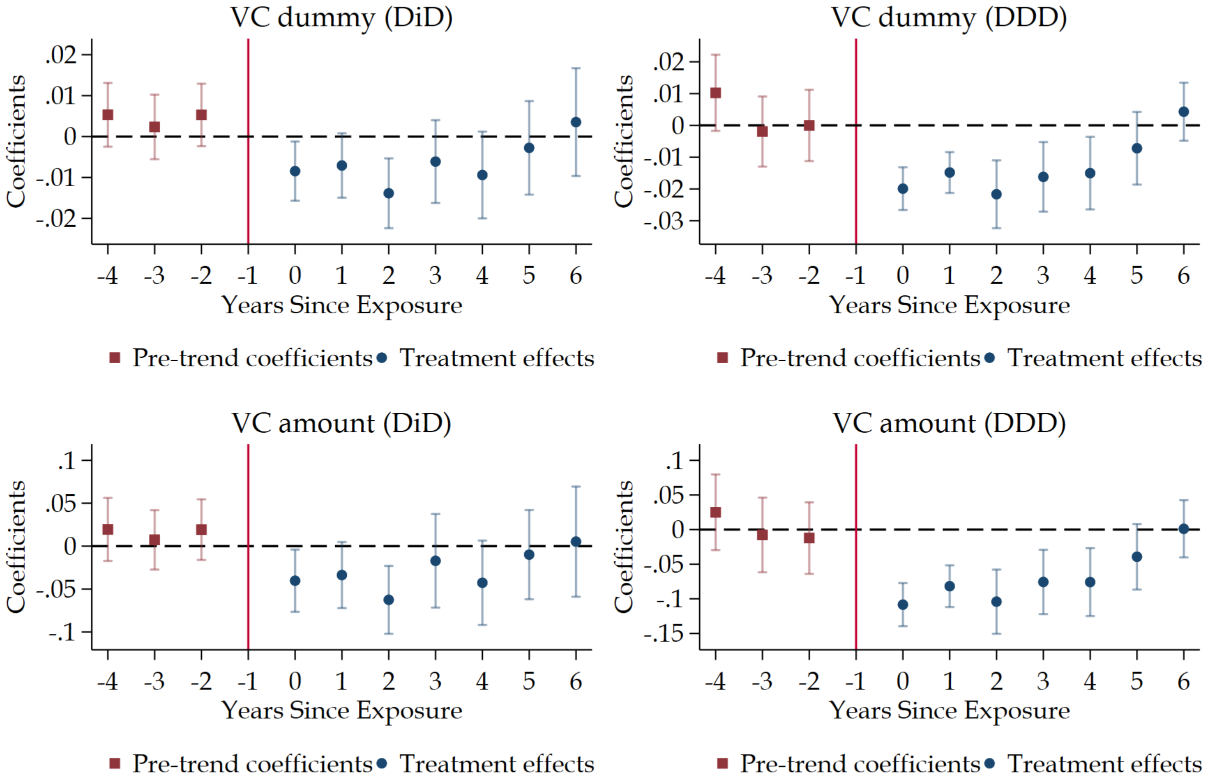


Figure 6: Academic Misconduct Exposure and VC investment

Notes: This figure presents event study results of academic misconduct exposure's effects on firms' venture capital financing in China from 2010 to 2021. Panel A shows the dynamic changes in the probability of receiving venture capital investment (*VC dummy*). Panel A1 reports results under a DiD specification, while Panel A2 presents DDD estimates incorporating a university collaboration decrease dummy (DUC) to identify firms that reduced university collaboration post-exposure. Panel B displays the dynamic changes in the IHS-transformed amount of venture capital investment (*VC amount*). Similarly, Panel B1 reports difference-in-differences results, while Panel B2 presents triple-difference estimates. Across all analyses, firms with pre-exposure patent collaboration relationships with misconduct-involved universities are identified as the treatment group. Red squares represent pre-exposure time trends between treatment and control groups, while solid blue circles represent treatment effects post-exposure. Bars indicate 95% confidence intervals with standard errors clustered at the firm level.

Recent literature demonstrates that traditional two-way fixed effects difference-in-differences (TWFE-DiD) estimators can produce biased estimates in the presence of staggered treatment timing (Goodman-Bacon, 2021). This bias primarily stems from treatment timing heterogeneity—in our context, cities and industries experiencing academic misconduct exposure at multiple times. Given that misconduct cases are disclosed successively from 2015 to 2021, city-industry combinations treated earlier serve as controls for later treatment groups. This setup may yield biased estimates if treatment effects exhibit temporal or unit-level heterogeneity.

To address this concern, we conduct robustness checks using recently developed econometric methods. Specifically, we re-estimate all analyses from Sections 4-6 using the robust estimators proposed in Borusyak et al. (2024); Cengiz et al. (2019); De Chaisemartin and d'Haultfoeuille (2020). These methods address the identification challenges of the overlap in treatment timing through distinct technical approaches (results reported in Appendix Figures A.1-A.4).

These robustness checks yield results highly consistent with our main findings: academic misconduct exposure significantly reduces firms' trust in universities, leads firms to shift toward inter-firm R&D alliances, and triggers adjustments in innovation characteristics and VC allocation. The robustness of estimates suggests our core findings are not driven by technical bias potentially arising from staggered DiD design.

7 Conclusion

This study examines how academic misconduct reshapes innovation networks through trust destruction in China from 2015 to 2021. We find that misconduct exposure significantly reduces firms' trust in affected universities, leading to decreased patent citations and collaborations. Firms respond by strategically increasing R&D alliances with other firms rather than internalizing R&D or seeking alternative university partners. This shift in collaboration patterns triggers systematic changes in innovation characteristics: reduced patent basicness but increased product orientation. The negative impact further propagates through innovation networks to capital markets, where VCs significantly reduce investments in firms that previously collaborated with universities affected by misconduct. These findings highlight trust's irreplaceable role in innovation governance and demonstrate how trust shocks can fundamentally reshape innovation networks through contractual adjustments and market responses. While our study focuses on academic misconduct, future research could explore various types of trust shocks across different institutional contexts and examine the psychological mechanisms underlying trust crises in innovation ecosystems.

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Appendix

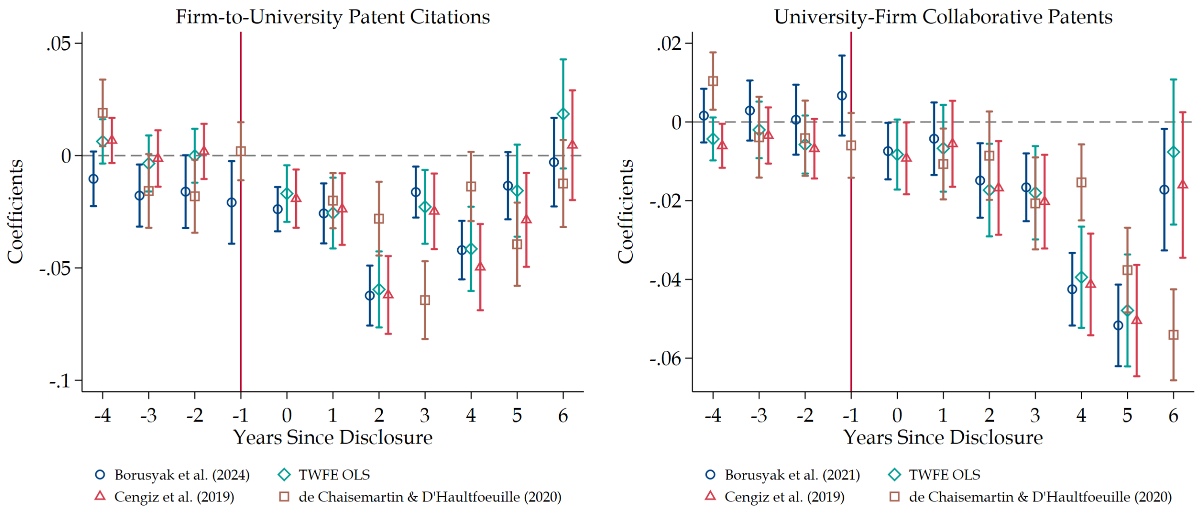

Figure A.1: Academic Misconduct Exposure and University-Industry Trust with Robust Estimators

Notes: This figure presents robustness tests using three estimation methods(Borusyak et al., 2024; Cengiz et al., 2019; De Chaisemartin and d'Haultfoeuille, 2020) for university-industry trust relationships. The left panel shows dynamic changes in firm-to-university patent citations, while the right panel displays changes in university-firm collaborative Patents. All variables are standardized within industry-year. The estimates demonstrate consistent treatment effects in direction and significance across different methods, supporting the robustness of our main findings. Error bars indicate 95% confidence intervals with standard errors clustered at the city-industry level.

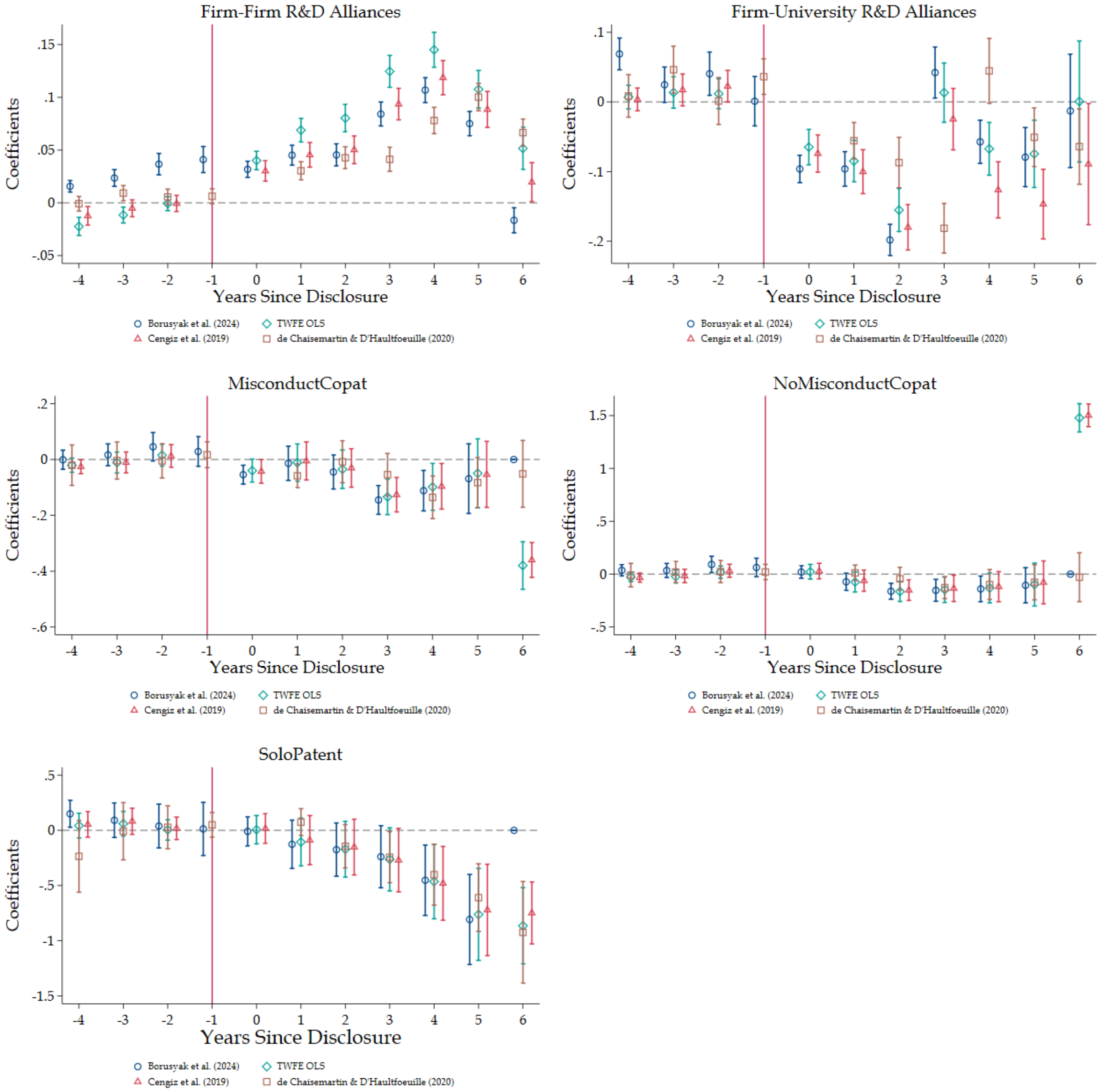

Figure A.2: Academic Misconduct Exposure and Innovation Network Reconfiguration with Robust Estimators

Notes: This figure employs three robust estimation methods (Borusyak et al., 2024; Cengiz et al., 2019; De Chaisemartin and d'Haultfoeuille, 2020) to examine dynamic changes in joint patent applications (CoPat, IHS-transformed). The empirical results show significant innovation network restructuring following academic misconduct exposure across different estimation methods, consistent with our main findings. Error bars indicate 95% confidence intervals with standard errors clustered at the innovation pair and firm level.

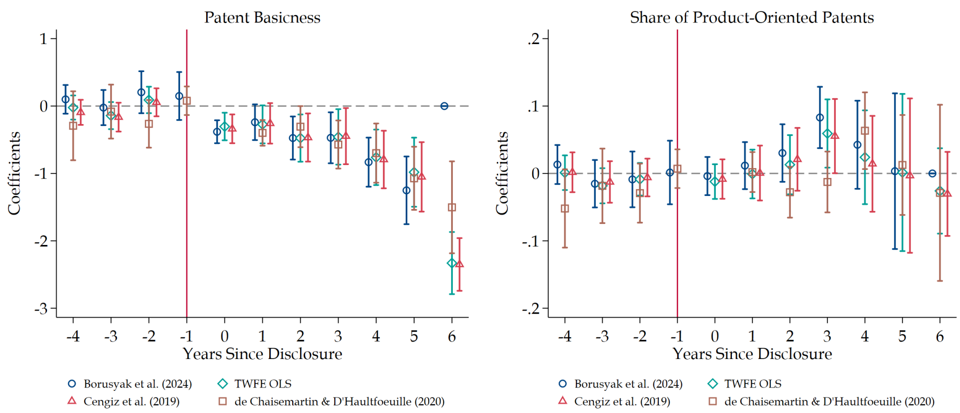

Figure A.3: Academic Misconduct Exposure and Innovation Characteristics with Robust Estimators

Notes: This figure presents tests using three robust estimation methods(Borusyak et al., 2024; Cengiz et al., 2019; De Chaisemartin and d'Haultfoeuille, 2020) for Patent Basicness and Share of Product-Oriented Patents. The empirical results demonstrate that academic misconduct exposure significantly reduces patent basicness while increasing the share of product-oriented patents across different estimation methods, validating the robustness of our main findings. Error bars indicate 95% confidence intervals with standard errors clustered at the firm level.

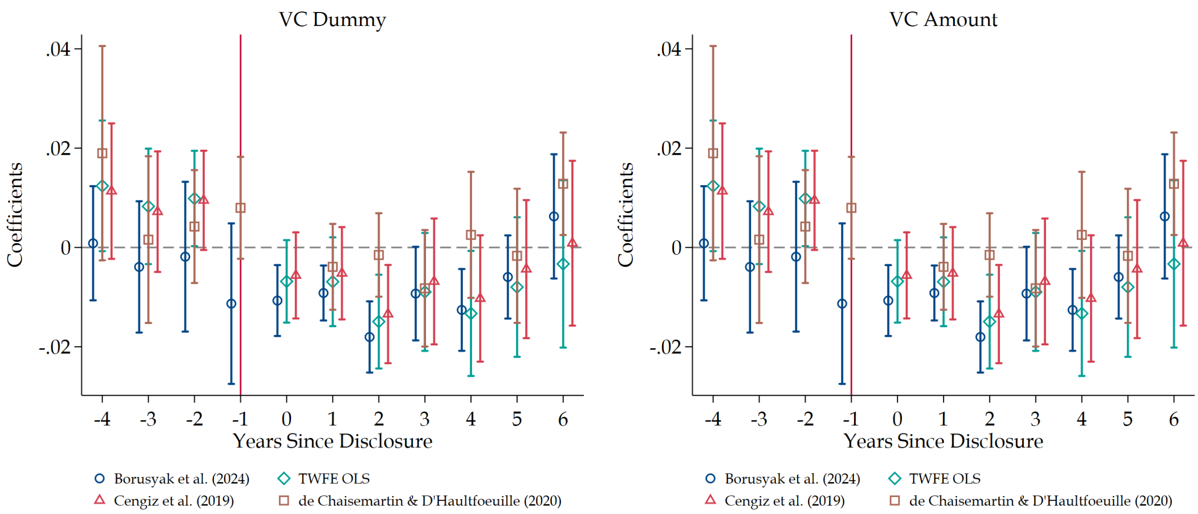

Figure A.4: Academic Misconduct Exposure and Venture Capital Investment with Robust Estimators

Notes: This figure reports tests using three robust estimation methods(Borusyak et al., 2024; Cengiz et al., 2019; De Chaisemartin and d'Haultfoeuille, 2020) for the probability of receiving venture capital investment and investment amount. The empirical results show that academic misconduct exposure significantly reduces both the likelihood and magnitude of venture capital investment for firms with pre-exposure collaboration relationships with misconduct-involved universities across different estimation methods, supporting the robustness of our main findings. Error bars indicate 95% confidence intervals with standard errors clustered at the firm level.

Table A.1: Mapping of NNSFC Disciplines to IPC Codes

NNSFC Discipline	International Patent Classification (IPC)
Chemical Sciences	A01N, A01P, A21D, A23B, A23C, A23D, A23J, A23K, A23L, A61Q, A62C, A62D, B01J, B09B, B09C, C02F, C03C, C05B, C05C, C05D, C05F, C05G, C06B, C06D, C06F, C07B, C07C, C07D, C07F, C07G, C07H, C07J, C07K, C08B, C08C, C08F, C08G, C08H, C08J, C08K, C08L, C09B, C09C, C09D, C09F, C09G, C09H, C09J, C10B, C10C, C10F, C10G, C10H, C10J, C10K, C10L, C10M, C11B, C11C, C11D, C12C, C12F, C12G, C12H, C12J, C12L, C12M, C13B, C13C, C13D, C13F, C13G, C13H, C13J, C13K, C14C, C25B, C25C, C25D, C25F, D01C, F42B, G03C, G21G, G21J, H01M
Life Sciences	A01G, A01H, A01J, A01K, C12N, C12Q, C12R
Earth Sciences	G01V, G01W
Engineering & Materials Sciences	A01B, A01C, A01D, A01F, A01L, A01M, A21B, A21C, A22B, A22C, A23N, A23P, A24B, A24C, A41H, A43D, A45D, A62B, A63B, B01B, B01F, B01L, B03B, B03C, B04B, B04C, B05B, B05C, B05D, B06B, B07B, B21B, B21C, B21D, B21F, B22C, B22D, B22F, B23B, B23C, B23D, B23F, B23G, B23H, B23K, B23P, B23Q, B24B, B24C, B24D, B25B, B25C, B25D, B25F, B25G, B25H, B25J, B26B, B26D, B26F, B27B, B27C, B27D, B27F, B27G, B27H, B27J, B27K, B27N, B28B, B28C, B28D, B29B, B29C, B29D, B29K, B31B, B31C, B31D, B31F, B32B, B41B, B41C, B41D, B41F, B41G, B41J, B41K, B41L, B44C, B44B, B60B, B60C, B60D, B60F, B60G, B60H, B60J, B60K, B60L, B60M, B60N, B60Q, B60R, B60T, B60V, B60W, B61B, B61C, B61D, B61F, B61G, B61H, B61J, B61K, B61L, B62B, B62C, B62D, B62H, B62J, B62K, B62L, B62M, B63B, B63C, B63G, B63H, B63J, B64B, B64C, B64D, B64F, B64G, B65B, B65C, B65F, B65G, B65H, B66B, B66C, B66D, B66F, B67D, B68F, B68G, B81B, B81C, B82B, B82Y, C03B, C03C, C04B, C06C, C06F, C09K, C14B, C21B, C21C, C21D, C23C, C23D, C23F, C23G, C30B, D01B, D01D, D01F, D01G, D01H, D02G, D02H, D03J, D05B, D05C, D06N, D21B, D21F, D21G, E01B, E01C, E01F, E02C, E02D, E02F, E03B, E03C, E03D, E03F, E04B, E04C, E04D, E04F, E04G, E04H, E05B, E05C, E05D, E05F, E06B, E21B, E21C, E21D, E21F, F01B, F01C, F01D, F01K, F01L, F01M, F01N, F01P, F02B, F02C, F02D, F02F, F02G, F02K, F02M, F02N, F02P, F03B, F03C, F03D, F03G, F03H, F04B, F04C, F04D, F04F, F15B, F15C, F15D, F16B, F16C, F16D, F16F, F16H, F16J, F16K, F16L, F16M, F16N, F16P, F16S, F16T, F17D, F21L, F21S, F21V, F21W, F22B, F22D, F22G, F23B, F23C, F23D, F23G, F23H, F23K, F23M, F23N, F23Q, F23R, F24B, F24C, F24D, F24F, F24H, F24J, F25B, F25C, F25D, F25J, F26B, F27B, F27D, F28B, F28C, F28D, F28F, F28G, F41A, F41B, F41C, F41F, F41G, F41H, F42C, G01B, G01C, G01D, G01F, G01G, G01H, G01J, G01K, G01L, G01M, G01N, G01P, G01Q, G01R, G01T, G02B, G02F, G03B, G03D, G03F, G04B, G04C, G04D, G04F, G04G, G04R, G05B, G05D, G05F, G05G, G06C, G06D, G06E, G06J, G07B, G07C, G07D, G07G, G08B, G09C, G10F, G10G, G10H, G10K, G12B, G21B, G21C, G21D, G21H, G21J, G21K, H01B, H01C, H01F, H01G, H01H, H01J, H01L, H01P, H01Q, H01R, H01S, H01T, H02B, H02G, H02H, H02J, H02K, H02M, H02N, H02P, H03B, H03C, H03D, H03F, H03G, H03H, H03L, H04Q, H04R, H04S, H04W, H05B, H05C, H05H, H05K
Information Sciences	G01S, G03G, G03H, G06F, G06G, G06K, G06M, G06N, G06Q, G06T, G08C, G08G, G09G, G10L, G11B, G11C, H03K, H03J, H03M, H04B, H04H, H04J, H04K, H04L, H04M, H04N, H04W
Medical Sciences	A61K, A61C, A61D, A61F, A61G, A61H, A61J, A61B, A61M, A61L, A61N, A61P

Notes: This table presents the correspondence between National Natural Science Foundation of China (NNSFC) disciplines and International Patent Classification (IPC) codes. Following Hall et al. (2001), this mapping enables industry-level matching between patent data and academic misconduct exposure data. Engineering and Materials Sciences covers the broadest range, spanning mechanical (Class B) to electrical engineering (Class H). Chemical Sciences primarily corresponds to Class C, while Life Sciences focuses on Classes A01 and C12. Information Sciences relates to computing and communication technology (Classes G and H). Medical Sciences concentrates on Class A61, and Earth Sciences primarily covers Classes G01V and G01W.

Table B.1: Classification of Product-related Technology Fields

Technological Field	International Patent Classification (IPC)
Agricultural Machinery	A01D, A01F, A01K
Medical Instruments and Apparatus	A61B, A61C, A61F, A61M
Chemical Process Apparatus	B01D, B01F, B01J
Machine Tools and Industrial Robots	B21D, B23K, B25J
Engines and Pumps	F01B, F02-F04
Mechanical Elements and Systems	F15B, F16, F17
Measuring and Testing Instruments	G01B, G01N, G01R
Optical and Photographic Apparatus	G02B, G02F, G03B
Computing and Control Systems	G06F, G07, G08
Vehicles and Transportation Systems	B60-B64
Electrical Components and Systems	H02-H05
Printing Machinery	B41
Material Handling and Packaging Machinery	B65-B67
Lighting and HVAC Apparatus	F21, F24-F25, F28
Display and Information Systems	G09-G12
Semiconductor Devices and Lasers	H01L, H01S

Notes: This table identifies product-oriented technological fields based on the first four digits of IPC codes. We classify 16 technological fields directly related to product development: Agricultural Machinery (e.g., A01D, A01F, A01K), Medical Equipment (e.g., A61B, A61C, A61F, A61M), Chemical Processing Equipment (e.g., B01D, B01F, B01J), Machine Tools and Industrial Robots (e.g., B21D, B23K, B25J), Engines and Pumps (F01B and F02-F04 classes), Mechanical Components and Systems (e.g., F15B, F16, F17 classes), Measurement and Testing Instruments (e.g., G01B, G01N, G01R), Optical and Photographic Equipment (e.g., G02B, G02F, G03B), Computing and Control Systems (e.g., G06F, G07, G08 classes), Transportation Systems (B60-B64 classes), Electrical Components (H02-H05 classes), Printing Machinery (B41 class), Material Handling and Packaging (B65-B67 classes), Lighting and HVAC Equipment (e.g., F21, F24-F25, F28 classes), Display Systems (G09-G12 classes), and Semiconductor Devices and Lasers (e.g., H01L, H01S). These fields characteristically produce innovations that directly manifest as tangible products or equipment with clear market applications. We use this classification system to calculate the share of product-oriented patents of firms as a measure of product orientation in innovation activities.