When Ideas become Mainstream? Theory and Empirical evidence from Econometrics Techniques

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Abstract

When do ideas become mainstream? Existing models predict that widely-cited innovations should be widely adopted, yet machine learning in economics generates explosive citations while remaining institutionally confined, and structural econometrics maintains the broadest networks despite declining usage. This paper demonstrates that diffusion operates independently across three levels—awareness, adoption, and spatial embedding—each governed by distinct mechanisms. Analyzing six econometric methods using 21,911 citations, 2,744 market observations, and 3,963 researchers (1950–2024), I find that awareness spreads smoothly through citations, but actual adoption faces substantial resistance varying 814-fold across methods. Machine learning grows fastest despite highest barriers because demonstrated value overcomes computational costs. Spatial diffusion varies 8-fold independent of usage patterns: structural econometrics achieves maximum institutional reach despite losing market share. Learning costs create 6.7-fold entry barriers; network effects generate 45-fold adoption increases. Effective innovation policy requires simultaneous intervention across awareness, adoption barriers, and institutional networks.

Keywords: Innovation Diffusion, Methodological Adoption, Reaction-Diffusion Models, Citation Dynamics, Market Share Competition, Institutional Networks, Spatial Diffusion

JEL Codes: O33, B41, D83, C63

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1 Introduction

When do ideas become mainstream? This question lies at the heart of scientific progress, yet existing diffusion models provide contradictory answers. Machine learning methods in economics generate explosive citation growth and rapid market share expansion, yet remain confined to a small network of specialized institutions. Structural econometrics exhibits the opposite pattern: declining market share coexists with sustained citation accumulation and the broadest institutional networks. Difference-in-differences maintains stable high market share while citations grow smoothly and institutional reach expands steadily. Standard diffusion models—designed to explain innovation adoption through a single S-curve—cannot reconcile these divergent patterns.

We argue that this confusion arises from conflating conceptually distinct diffusion processes. Ideas do not simply "diffuse"—they traverse multiple levels from awareness to adoption to institutional embedding, each governed by different mechanisms and operating on different timescales. Citations measure *awareness*, market shares measure *usage*, and institutional networks measure *spatial reach*. Existing approaches collapse these dimensions into a single measure, obscuring the multi-stage process through which innovations become mainstream.

This paper makes three contributions to understanding innovation diffusion in knowledge-intensive environments. First, we develop a reaction-diffusion framework with microfoundations linking diffusion parameters to economic primitives. The intrinsic adoption rate r reflects method value and network effects, resistance β aggregates learning and computational costs, and spatial diffusion D emerges from institutional collaboration networks. This microfounded approach enables precise interpretation of diffusion dynamics and prediction of policy effects. Empirical validation using 3,963 economists' career trajectories confirms that learning costs create measurable entry barriers—87.3% of researchers adopt difference-in-differences first versus 13.0% for synthetic control—and that network effects dominate adoption decisions, with peer usage generating up to 45-fold increases in individual adoption rates.

Second, we extend the framework to competitive settings where multiple methods vie for researcher attention. The competitive dynamics model introduces a substitution parameter γ_{ij} capturing the intensity of competition between methods i and j. We derive conditions for coexistence versus exclusion, showing that stable coexistence requires $(r_A - \beta_A)(r_B - \beta_B) > \gamma_{AB}\gamma_{BA}$. Empirical analysis reveals level-dependent competition: credibility revolution methods complement within papers (15.8% co-occurrence for DiD and RDD) but researchers specialize across careers (correlation of -0.303 between structural and natural experiments).

Third, we demonstrate that diffusion operates independently across three levels: awareness, adoption, and spatial reach. Existing approaches conflate these dimensions, leading to paradoxical findings where widely-cited methods decline in usage. Our multi-level validation resolves these puzzles by showing that parameters operate on different timescales—awareness spreads rapidly through publications ($\beta \approx 0$), adoption faces persistent barriers requiring infrastructure investment ($\beta \in [0, 0.814]$), and spatial diffusion builds slowly through collaborative networks ($D \in [0.123, 0.998]$). This independence explains why machine learning ranks first in citation velocity and market share growth but only fifth in spatial diffusion, while structural econometrics shows the inverse pattern.

We validate the framework using comprehensive data on six econometric methods spanning 1950-2024: Google Ngrams tracking paradigm terminology (1950-2022), OpenAlex citations measuring awareness diffusion for five seminal papers (N=21,911, 1925-2025), and full-text keyword search capturing actual usage in 30,000+ economics papers (2011-2024). At the paradigm level, structural econometrics and the credibility revolution exhibit sequential replacement—adoption rate peaks separated by 17 years—with both facing minimal resistance ($\beta \approx 0$). Citation analysis confirms smooth awareness diffusion ($R^2 > 0.98$ for all methods), with accumulation rates varying threefold. Market share analysis reveals substantial adoption resistance, with machine learning achieving $r = 0.890$ despite $\beta = 0.814$. Network analysis demonstrates independence: structural econometrics achieves maximum spatial reach ($D = 0.998$) despite declining market share, while machine learning shows explosive temporal growth yet moderate spatial diffusion ($D = 0.362$).

The empirical findings resolve an apparent paradox: how can structural econometrics papers accumulate citations smoothly, maintain the broadest institutional networks, yet lose market share? The answer lies in the independence of diffusion levels. Citations measure knowledge dissemination, market shares measure usage patterns, and networks measure institutional embedding. Decades of collaboration create persistent structures that outlast usage declines. Single-measure approaches miss these dynamics entirely, conflating awareness with adoption and temporal growth with spatial reach.

Our framework generates precise policy guidance. For paradigm shifts, policy should focus on demonstration effects—the credibility revolution succeeded because transparent identification strategies resolved skepticism about causal inference. For awareness diffusion, conference presentations and citation networks suffice. For adoption, interventions must reduce learning costs through training programs and improved software while activating network effects. The 45-fold network effect we document suggests that strategic seeding may prove more cost-effective than broad dissemination. For spatial diffusion, building institutional networks requires patient investment in collaborative relationships that accumulate slowly and persist even when methods decline in usage.

These insights challenge current research evaluation practices. Citation-based metrics conflate awareness with adoption, creating misleading signals about actual usage. Methods losing market share can maintain citation growth, as structural econometrics demonstrates. Evaluation systems rewarding citation accumulation may inadvertently discourage methodological innovation by failing to distinguish conceptual influence from practical application.

The paper proceeds as follows. Section 2 reviews existing diffusion models and explains why single-level approaches fail to capture innovation dynamics in knowledge-intensive settings. Section 3 develops the theoretical framework, providing microfoundations for diffusion parameters and extending to competitive dynamics. Section 4 validates the framework across paradigm terminology, awareness through citations, actual usage in market shares, and spatial diffusion through institutional networks. Section 4.7 validates theoretical microfoundations using researchers' career trajectories. Section 5 concludes with policy implications for accelerating innovation adoption.

2 Literature Review

This paper contributes to three interconnected literatures: classical diffusion models that provide foundational mechanisms, economic theories of idea flows and knowledge spillovers, and recent work in the science of science examining how innovations spread through academic networks. Our framework integrates insights from these traditions while addressing a critical gap: existing approaches model diffusion through a single aggregate measure, conflating conceptually distinct processes—awareness, adoption, and spatial embedding—that operate independently on different timescales. We develop a multi-level framework that separates these mechanisms, generates testable predictions about their independence, and provides microfoundations linking diffusion parameters to observable economic primitives.

2.1 Classical Diffusion Models

The Bass diffusion model (Bass, 2004) provides the canonical framework for modeling innovation adoption, decomposing the process into innovation (independent adoption) and imitation (socially influenced adoption). This parsimonious two-parameter specification successfully predicts S-curve adoption patterns across diverse domains from consumer durables (Dowling, 1980) to technological standards (Fibich and Golan, 2023). However, the Bass model assumes a single homogeneous population with uniform dynamics, precluding analysis of competing innovations or spatial heterogeneity in adoption rates (Kotthoff and Hamacher, 2022).

Epidemiological SIR (Susceptible-Infected-Recovered) models (Kermack and McKendrick, 1927; Wilson and Worcester, 1945) have been adapted to study idea diffusion by treating concepts as "contagions" spreading through social contact. These models illuminate the role of transmission rates and recovery dynamics, finding extensive application in public health contexts (Trejo and Hengartner, 2022; Acemoglu et al., 2021). Yet traditional SIR frameworks encounter difficulties when multiple competing ideas interact—as in political polarization or scientific paradigm competition—and typically assume population homogeneity that obscures heterogeneous adoption barriers (Bansal et al., 2007).

Spatial diffusion models (Rogers, 1993; Bernards et al., 2016) extend classical frameworks to account for geographic spread, documenting that innovations often exhibit center-periphery patterns with adoption accelerating in dense urban networks before reaching isolated communities. While these contributions demonstrate the importance of spatial factors, they remain primarily descriptive and applicative rather than providing theoretical foundations for why spatial and temporal diffusion might operate independently.

Our framework builds on these foundations by explicitly modeling resistance factors that generate heterogeneous barriers across adoption stages, incorporating competitive dynamics between multiple coexisting ideas, and—critically—demonstrating through both theory and evidence that awareness diffusion (citations), usage adoption (market shares), and spatial embedding (institutional networks) follow distinct dynamics that cannot be reduced to a single S-curve.

2.2 Network-Based Diffusion and Social Influence

A parallel literature emphasizes network structure as fundamental to diffusion processes. Granovetter (1973) demonstrates that weak ties—connections spanning different social clusters—prove more valuable than strong ties for information transmission, as they provide access to non-redundant knowledge. Watts and Strogatz (1998) show that "small-world" networks combining high local clustering with sparse long-distance connections accelerate diffusion relative to either purely random or purely regular network topologies.

Strategic models of influence maximization (Kempe et al., 2003) identify optimal seeding strategies for cascading adoption, finding that targeting high-centrality individuals ("influencers") generates substantially larger cascades than random seeding. Dodds and Watts (2004) generalize these insights, demonstrating that diffusion dynamics depend critically on threshold distributions—the fraction of peers who must adopt before an individual follows suit. These network-based approaches provide valuable insights into how local structure shapes global diffusion patterns.

Recent empirical work exploits quasi-experimental variation to identify peer effects in knowledge production. Waldinger (2012) leverages dismissals of Jewish scientists in Nazi Germany to estimate peer effects of 0.3 standard deviations in productivity. Azoulay et al. (2010) find that collaborators experience 5–8% productivity declines following superstar deaths, with effects concentrated among coauthors who had not yet established independent research programs. Borjas and Doran (2012) document that American mathematicians working in Soviet-dominated subfields experienced significant productivity gains following the USSR's collapse and the influx of Soviet émigrés.

König et al. (2022) provide a comprehensive synthesis of how R&D networks shape knowledge spillovers, emphasizing that spatial and temporal diffusion operate through distinct channels. Our framework integrates this insight by modeling spatial diffusion coefficient D separately from temporal adoption parameters r and β, predicting—and empirically confirming—near-zero correlation between temporal growth rates and spatial reach.

We contribute to this literature by providing microfoundations for network effects in the adoption rate ($r = \alpha_V \cdot V + \alpha_\theta \cdot \theta$) and demonstrating empirically that peer influence generates 45-fold increases in adoption when coauthor usage intensifies from 0–25% to 75–100%. This magnitude substantially exceeds prior estimates, likely because we examine methodological adoption—where coordination benefits are strong—rather than research productivity spillovers.

2.3 Economic Models of Idea Flows and Technology Diffusion

Economic growth theory provides complementary perspectives on how ideas spread across firms, sectors, and countries. Lucas Jr and Moll (2014) develop a model where time allocation between knowledge production and consumption determines long-run growth, with older researchers specializing in knowledge application while younger cohorts focus on creation. This life-cycle pattern parallels our finding that method adoption varies systematically with career stage: 87.3% of difference-in-differences users adopt the technique early career, compared to only 13.0% for synthetic control.

Perla and Tonetti (2014) model growth through imitation: firms observe productivity distributions among trading partners and adopt superior technologies probabilistically. Their framework predicts that openness accelerates growth by expanding the set of observable techniques, generating long-run productivity gains through selection and learning. Buera and Oberfield (2020) extend this mechanism internationally, showing that trade integration increases the flow of ideas across borders and generates convergence in technological capabilities.

Sampson (2015) analyzes dynamic selection in technology diffusion, demonstrating that firms with superior technology grow faster and survive longer, while laggards exit or adopt frontier techniques. This selection mechanism creates path-dependent diffusion where early advantages compound over time. Bloom et al. (2013) develop methods to separate technology spillovers from product market rivalry, distinguishing complementary from substitutive effects—a distinction central to our competitive dynamics model with parameter γ_{ij}.

Alvarez et al. (2008) provide a general framework for idea flows emphasizing both micro-level adoption decisions and macro-level diffusion patterns. They highlight that barriers to adoption—learning costs, coordination failures, institutional rigidities—generate heterogeneous diffusion speeds across contexts. Our microfoundation $\beta = \alpha_L \cdot c_L + \alpha_C \cdot c_C$ formalizes this intuition, decomposing resistance into learning and computational components that we measure empirically.

We extend this literature by providing a tractable framework for measuring adoption barriers directly from observed diffusion patterns, validating that resistance varies 814-fold across usage contexts ($\beta \in [0, 0.814]$) despite uniform zero resistance in awareness contexts ($\beta \approx 0$). This multi-level approach clarifies why awareness campaigns often fail to accelerate adoption: the binding constraint lies in usage barriers, not information transmission.

2.4 Science of Science and Methodological Change

Recent work in the "science of science" literature examines meta-patterns in knowledge production. Park et al. (2023) document that scientific papers and patents are becoming less disruptive over time, with new work increasingly building on narrow foundations rather than synthesizing across domains. Chu and Evans (2021) show that canonical progress—the rate at which new papers become highly cited—has slowed in large scientific fields, attributed to increasing competition for attention and higher barriers to achieving breakthroughs as fields mature.

Packalen and Bhattacharya (2020) argue that scientific incentives increasingly favor incremental refinement over exploration of new ideas, as funding agencies and journals reward work building on established foundations. They show that new ideas take longer to diffuse into mainstream research agendas, with adoption timescales lengthening over recent decades. These patterns align with our finding that structural econometrics—a mature methodology—exhibits near-zero adoption growth ($r \approx 0$) despite sustained citation accumulation and maximum spatial reach ($D = 0.998$).

Ahmadpoor and Jones (2017) analyze the relationship between scientific advances and subsequent patenting, finding that patents typically follow scientific publications with lags of 5–15 years depending on domain. This temporal separation between knowledge creation and technological application parallels our distinction between awareness (citations) and adoption (usage): knowing a technique exists differs fundamentally from investing in its application.

Cheng et al. (2023) examine diffusion of new scientific concepts, identifying social embeddedness and ideational coherence as complementary mechanisms. Ideas gain traction when both socially prominent researchers adopt them and when they integrate coherently with existing conceptual frameworks. Our framework formalizes this duality: the adoption rate r captures demonstrated value and network effects (social embeddedness), while resistance β reflects barriers from incompatibility with existing practices (inverse of ideational coherence).

In the economics discipline specifically, Angrist and Pischke (2010) articulate the "credibility revolution"—a paradigm shift toward transparent identification strategies emphasizing natural experiments, regression discontinuity, and randomized controlled trials. Leamer (2010) offers a skeptical counterpoint, arguing that methodological fashion can outpace genuine improvements, with researchers adopting techniques to signal sophistication rather than because they solve substantive problems. Athey (2018) surveys machine learning applications in economics, documenting rapid adoption despite substantial computational barriers.

Our empirical application contributes to this literature by providing systematic measurement of methodological diffusion dynamics. We document that the credibility revolution paradigm adopts twice as fast as structural econometrics ($r = 1.000$ versus $r = 0.537$) with negligible resistance in both cases ($\beta \approx 0$), validating that paradigm shifts face minimal barriers once awareness spreads. At the method level, machine learning achieves highest adoption rate ($r = 0.890$) despite highest resistance ($\beta = 0.814$), demonstrating that demonstrated value can overcome computational barriers—supporting Athey (2018)'s optimistic assessment over Leamer (2010)'s skepticism.

2.5 Contribution and Positioning

Our framework makes three contributions relative to existing literatures. **First**, we demonstrate theoretically and empirically that diffusion operates independently across levels—awareness, adoption, and spatial embedding—each governed by distinct mechanisms and operating on different timescales. Classical diffusion models conflate these stages into a single S-curve; we show this aggregation obscures fundamental dynamics and generates misleading inferences about diffusion success. Methods can be widely known ($\beta_{\text{citations}} \approx 0$) yet face substantial adoption barriers ($\beta_{\text{usage}} \in [0, 0.814]$), and rapid temporal growth ($r = 0.890$) need not translate to broad spatial reach ($D = 0.362$).

Second, we provide microfoundations linking reduced-form diffusion parameters to observable economic primitives: method value V, learning costs c_L, computational costs c_C, network effects θ, and collaboration intensity γ. This decomposition enables precise interpretation of parameter estimates—resistance β measures learning and computational barriers, not intrinsic method quality—and generates testable predictions about researcher behavior that we validate using individual career trajectories. We document that learning costs create 6.7-fold entry barriers (87.3% versus 13.0% first-adoption rates) and network effects generate 45-fold adoption increases, magnitudes that inform optimal policy design.

Third, we extend competitive dynamics models to allow context-dependent competition: methods may complement within papers (researchers use multiple techniques for robustness, generating $\gamma_{ij} < 0$) while researchers specialize across careers (developing expertise in particular approaches, generating $\gamma_{ij} > 0$). This reconciles seemingly contradictory patterns—credibility revolution methods exhibit 15.8% co-occurrence within papers yet negative career correlations ($r = -0.303$ for structural versus natural experiments)—and clarifies that competition structure depends on the level of analysis.

The framework thus provides a unified approach to measuring, interpreting, and predicting innovation diffusion in knowledge-intensive environments where awareness, adoption, and institutional embedding follow distinct dynamics requiring separate interventions.

3 Theoretical Framework

The diffusion of new ideas within a community can be described as a dynamic process in which individuals adopt innovative concepts over time, influenced by internal adoption incentives and external pressures. This section develops a reaction-diffusion framework that integrates three key mechanisms: temporal adoption dynamics governed by individual decision-making, resistance arising from adoption barriers, and spatial diffusion through institutional networks. Unlike existing models that treat diffusion parameters as exogenous, we provide microfoundations linking these parameters to underlying economic primitives, enabling testable predictions about how interventions affect diffusion outcomes.

3.1 Model Setup

Consider a population of researchers distributed across locations indexed by x. At time t, the proportion of researchers at location x who have adopted the new methodological approach is denoted $p(x,t)$, where $0 \leq p(x,t) \leq 1$. The evolution of $p(x,t)$ follows a partial differential equation incorporating temporal adoption dynamics, resistance to change, and spatial diffusion across institutional networks.

3.2 Temporal Dynamics of Adoption

We begin with the baseline logistic growth model, where the rate of change in adoption depends on both the current adoption level and the remaining potential for adoption. The temporal dynamics are governed by

$$\frac{\partial p}{\partial t} = r\, p(x,t)\,(1 - p(x,t)), \tag{1}$$

where $r > 0$ represents the intrinsic adoption rate. The logistic formulation ensures that adoption accelerates when p is small, reaches maximum velocity at $p = 0.5$, and decelerates as saturation approaches. This specification captures the empirical regularity that innovations exhibit S-shaped diffusion curves, consistent with both theoretical predictions and observed patterns in technology adoption.

3.3 Incorporating Resistance to Adoption

Real-world diffusion processes face barriers that impede adoption even when methods offer genuine improvements. We model resistance as a parameter $\beta \geq 0$ that reduces the adoption rate proportionally to the current adoption level:

$$\frac{\partial p}{\partial t} = r\, p(x,t)\,(1 - p(x,t)) - \beta\, p(x,t). \tag{2}$$

The resistance term $-\beta p(x,t)$ captures the ongoing costs that adopters face, including learning costs, computational requirements, and institutional inertia. Larger values of β represent stronger barriers such as entrenched curriculum requirements, absence of complementary infrastructure, or network effects favoring incumbent methods.

The feasibility of adoption depends critically on the balance between adoption incentives and barriers. At steady state with $\frac{\partial p}{\partial t} = 0$, the system admits two equilibria: $p = 0$ (complete rejection) and

$$p^* = 1 - \frac{\beta}{r}. \tag{3}$$

The equilibrium p^* exists and is stable if and only if $r > \beta$. When adoption incentives fail to exceed barriers ($r \leq \beta$), the new idea cannot gain traction and the population remains at $p = 0$. This threshold condition has important policy implications: interventions must either increase adoption incentives r through demonstrations of value, reduce barriers β through infrastructure investment and training, or pursue both strategies simultaneously.

3.4 Spatial Diffusion of Ideas

Ideas propagate not only through time but also across geographic and institutional space. We incorporate spatial diffusion through a standard diffusion term:

$$\frac{\partial p}{\partial t} = D\frac{\partial^2 p}{\partial x^2} + r\,p(x,t)\,(1 - p(x,t)) - \beta\,p(x,t), \tag{4}$$

where $D \geq 0$ quantifies the rate of spatial spread. This reaction-diffusion equation couples local adoption dynamics with spatial propagation, capturing how ideas spread through collaborative networks, conference interactions, and institutional ties. High values of D enable rapid geographic expansion, while low values confine adoption to isolated clusters, prolonging the period of heterogeneous adoption across locations.

3.5 Equilibrium and Stability Analysis

At spatial equilibrium, the system satisfies

$$D\frac{\partial^2 p}{\partial x^2} + r\,p(x)\,(1 - p(x)) - \beta\,p(x) = 0. \tag{5}$$

For the homogeneous case with $D = 0$, we obtain equilibria $p = 0$ and $p^* = 1 - \beta/r$ as previously derived. Linearizing around these equilibria yields eigenvalues $\lambda_0 = r - \beta$ for the zero equilibrium and $\lambda^* = -(r - \beta)$ for the positive equilibrium. Thus $p = 0$ is stable when $r < \beta$, while p^* is stable when $r > \beta$, confirming that successful diffusion requires adoption incentives to exceed resistance.

For the spatial case with $D > 0$, traveling wave solutions exist when $r > \beta$, allowing ideas to propagate across geographic regions. The minimum wave speed is $c_{min} = 2\sqrt{D(r - \beta)}$, indicating that spatial diffusion depends on both the diffusion coefficient and the net adoption rate. This relationship suggests that policies targeting only temporal adoption (increasing r or decreasing β) have limited impact unless spatial networks (captured by D) facilitate geographic spread.

3.6 Microfoundations of Diffusion Parameters

The reduced-form parameters r, β, and D arise from underlying researcher decisions and institutional structures. We now provide microfoundations linking these parameters to observable economic primitives, enabling more precise interpretation of empirical estimates.

Consider a researcher deciding whether to adopt a new methodological approach. Adoption yields expected benefits V in terms of publication opportunities, citation returns, and career advancement. However, adoption requires upfront investment in learning the method, denoted c_L, and may impose ongoing computational costs c_C for software, hardware, or data requirements. In environments where social influence matters, peer adoption generates additional returns $\theta \cdot \bar{p}$, where $\bar{p}$ represents the adoption rate among a researcher's professional network and θ captures network effects.

A researcher adopts when the net present value exceeds continuation with existing methods:

$$V - c_L - c_C + \theta \cdot \bar{p} > 0. \tag{6}$$

The adoption probability at time t follows a logistic specification:

$$P(\text{adopt at } t) = \frac{\exp(V - c_L - c_C + \theta \cdot \bar{p}(t))}{1 + \exp(V - c_L - c_C + \theta \cdot \bar{p}(t))}. \tag{7}$$

Aggregating across researchers and taking a first-order approximation near $p = 0$ yields the intrinsic adoption rate

$$r = \alpha_V \cdot V + \alpha_\theta \cdot \theta, \tag{8}$$

where α_V and α_θ are positive coefficients reflecting the sensitivity of adoption to returns and network effects. The resistance parameter emerges as

$$\beta = \alpha_L \cdot c_L + \alpha_C \cdot c_C, \tag{9}$$

where α_L and α_C convert costs into effective resistance.

This microfoundation clarifies the economic interpretation of our parameters. The intrinsic adoption rate r reflects both the fundamental value proposition of the new method (captured by V) and social multiplier effects (θ). Resistance β aggregates learning barriers and computational requirements. The equilibrium adoption level $p^* = 1 - \beta/r$ can thus be rewritten as

$$p^* = 1 - \frac{\alpha_L c_L + \alpha_C c_C}{\alpha_V V + \alpha_\theta \theta}, \tag{10}$$

revealing that widespread adoption requires either low adoption costs or sufficiently high returns and network effects.

The spatial diffusion coefficient D emerges from the structure of collaborative networks. Let N_{ij} denote the number of collaborative ties between institutions i and j, and let d_{ij} represent geographic or social distance. The diffusion coefficient follows

$$D = \gamma \sum_{j} \frac{N_{ij}}{d_{ij}^2}, \tag{11}$$

where $\gamma > 0$ is a scaling parameter. Institutions with dense collaborative networks and short distances exhibit high D, facilitating rapid spatial diffusion. This formulation explains why methods adopted by well-connected research centers spread faster than those emerging from isolated institutions.

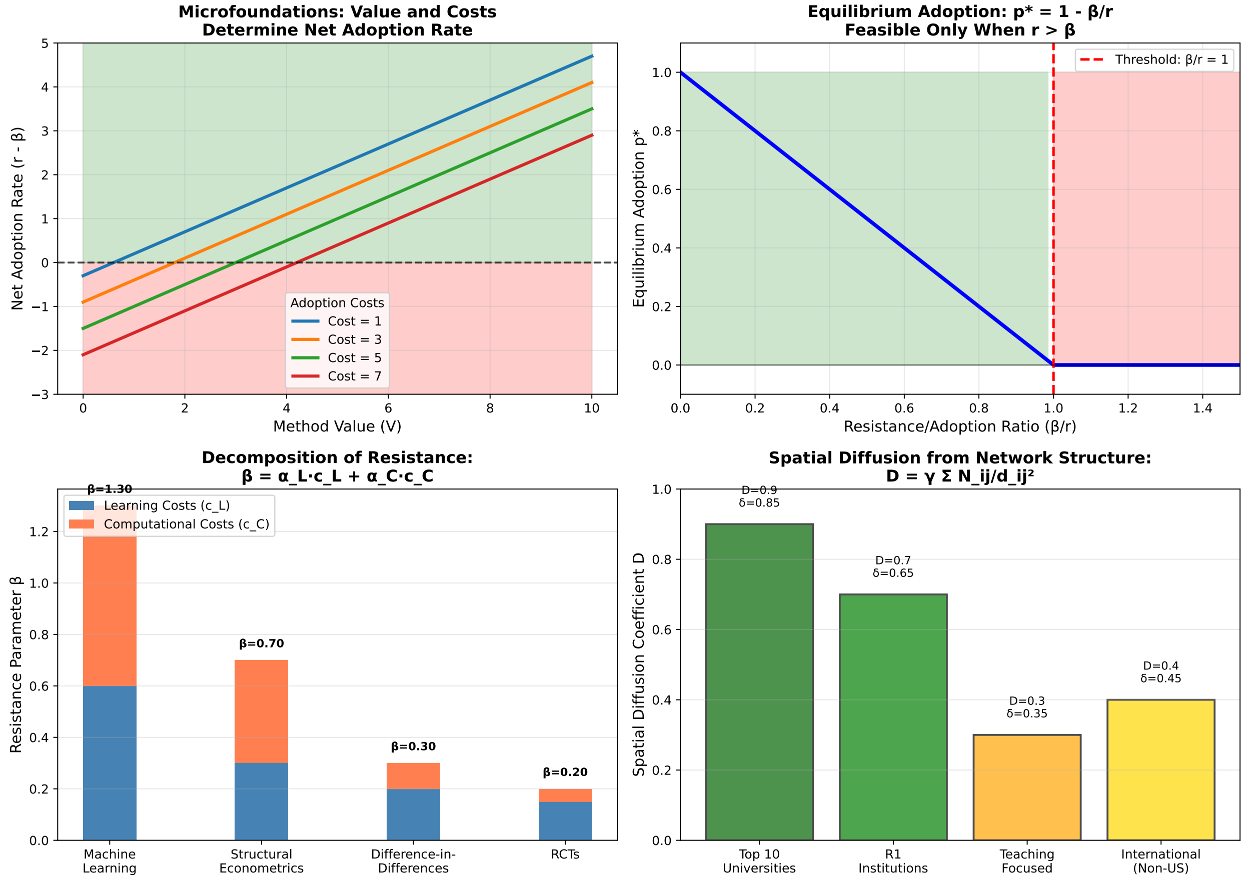

Figure 1: Microfoundations of Diffusion Parameters. **Panel A (top-left)**: Net adoption rate $(r - \beta)$ as a function of method value V for different cost levels. Higher costs shift the curve downward, requiring greater value to achieve positive net adoption. **Panel B (top-right)**: Equilibrium adoption $p^* = 1 - \beta/r$ as a function of the resistance-to-adoption ratio. Adoption is feasible only when $\beta/r < 1$ (shaded green region). **Panel C (bottom-left)**: Decomposition of resistance parameter β into learning costs c_L and computational costs c_C for four methods. Machine learning exhibits highest total resistance from substantial requirements in both dimensions. **Panel D (bottom-right)**: Spatial diffusion coefficient D across institutional types, reflecting network density δ and collaborative structure. Well-connected research universities achieve highest D, facilitating rapid geographic spread.

3.7 Competitive Dynamics Between Ideas

When multiple methodological approaches compete for researcher attention and journal space, adoption of one method may reduce the likelihood of adopting alternatives. We extend the baseline model to capture competitive interactions between methods. Let $p_i(x, t)$

denote the adoption rate of method i at location x and time t. The dynamics follow

$$\frac{\partial p_i}{\partial t} = D_i \frac{\partial^2 p_i}{\partial x^2} + r_i p_i (1 - p_i) - \beta_i p_i - \sum_{j \neq i} \gamma_{ij} p_j p_i, \tag{12}$$

where γ_{ij} captures the competitive intensity between methods i and j. When $\gamma_{ij} > 0$, methods are substitutes: adoption of method j reduces the net growth rate of method i. When $\gamma_{ij} < 0$, methods are complements, used together in the same research projects. The case $\gamma_{ij} = 0$ corresponds to independent diffusion.

The competition parameter γ_{ij} has clear empirical content. Methods addressing similar research questions with overlapping applications exhibit positive γ_{ij}, generating competitive displacement. Methods requiring similar technical skills or computational infrastructure may also compete for the same pool of potential adopters. Conversely, methods that complement each other in research workflows (such as using difference-in-differences for identification alongside machine learning for prediction) exhibit negative γ_{ij}.

In the two-method case with methods A and B, the coupled system becomes

$$\frac{\partial p_A}{\partial t} = r_A p_A (1 - p_A) - \beta_A p_A - \gamma_{AB} p_B p_A, \tag{13}$$

$$\frac{\partial p_B}{\partial t} = r_B p_B (1 - p_B) - \beta_B p_B - \gamma_{BA} p_A p_B. \tag{14}$$

At interior equilibrium where both methods coexist, we require $\frac{\partial p_A}{\partial t} = \frac{\partial p_B}{\partial t} = 0$. Solving yields equilibrium adoption levels

$$p_A^* = \frac{r_A - \beta_A - \gamma_{AB} p_B^*}{r_A}, \tag{15}$$

$$p_B^* = \frac{r_B - \beta_B - \gamma_{BA} p_A^*}{r_B}. \tag{16}$$

Stable coexistence occurs when both methods can sustain positive adoption despite competition. The condition for coexistence requires

$$(r_A - \beta_A)(r_B - \beta_B) > \gamma_{AB} \gamma_{BA}. \tag{17}$$

When competitive effects are weak ($\gamma_{AB}, \gamma_{BA} \approx 0$), methods coexist provided both satisfy $r_i > \beta_i$ individually. Strong competition can drive one method to extinction even if both would succeed in isolation, a phenomenon relevant for understanding paradigm shifts where new approaches displace established methods despite the latter maintaining intrinsic viability.

The competitive framework generates testable predictions. First, methods with higher adoption rates and lower resistance should capture larger equilibrium market shares. Second, sequential introduction of methods creates first-mover advantages: the first method to achieve substantial adoption imposes competitive pressure on subsequent entrants through the $\gamma_{ij}p_jp_i$ term. Third, complementary methods (negative γ_{ij}) should exhibit positive correlation in adoption patterns, while substitutes show negative correlation.

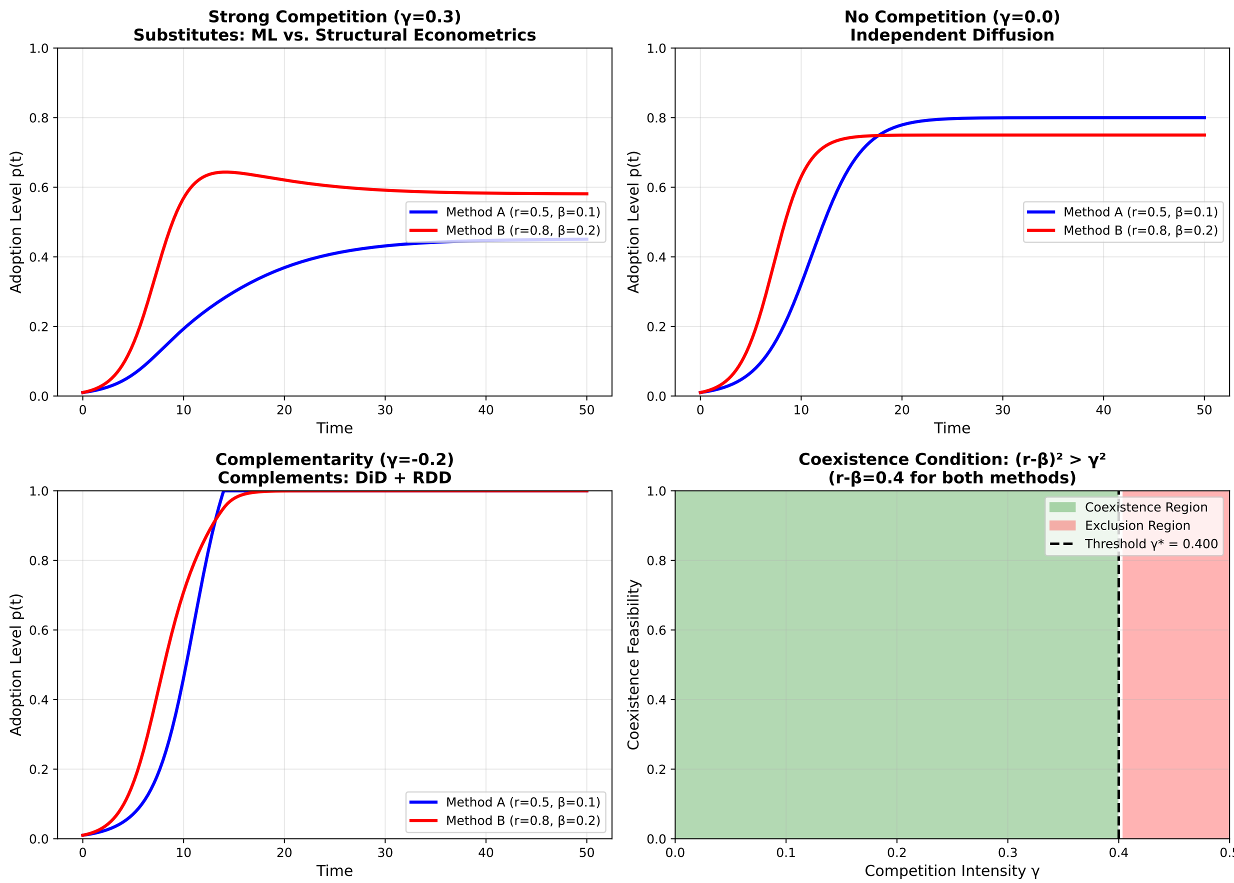

Figure 2: Competitive Dynamics Between Methods. **Panel A (top-left)**: Strong competition ($\gamma_{AB} = \gamma_{BA} = 0.3$) where Method B with higher adoption rate dominates Method A, illustrating competitive exclusion as observed between machine learning and structural econometrics. **Panel B (top-right)**: Independent diffusion ($\gamma = 0$) where both methods coexist without competitive effects, each achieving equilibrium determined solely by intrinsic parameters r and β. **Panel C (bottom-left)**: Complementarity ($\gamma < 0$) where methods reinforce each other's adoption, as observed for difference-in-differences and regression discontinuity designs used jointly. **Panel D (bottom-right)**: Phase diagram showing feasibility of coexistence as a function of competitive intensity γ. Coexistence requires $\gamma < \sqrt{(r_A - \beta_A)(r_B - \beta_B)}$; beyond this threshold (vertical dashed line), competitive exclusion drives one method to extinction despite both being intrinsically viable.

3.8 Characterization of Diffusion Parameters

The integrated framework highlights three dimensions of diffusion operating on distinct timescales. First, the temporal adoption rate r governs how quickly individual researchers adopt new methods, operating on a scale of months to years. This rate reflects both intrinsic method quality and demonstration effects. Second, resistance β captures persistent barriers to adoption including learning costs and institutional inertia, which may remain stable over years or even decades. Third, spatial diffusion D determines geographic and institutional spread, operating over extended periods as collaborative networks form and dissolve.

The intrinsic adoption rate r reflects the baseline tendency to adopt new methodological approaches. High values indicate strong demonstrated value through successful applications, clear advantages over alternatives, and active promotion by influential researchers. Methods with high r exhibit rapid initial diffusion once awareness spreads. Low values suggest that adoption requires significant external support through training programs, software development, or institutional mandates.

The resistance parameter β encompasses multiple sources of adoption barriers. Learning costs arise from the time investment required to achieve proficiency with new techniques, including mastering new software environments, understanding theoretical foundations, and developing practical implementation skills. Computational barriers include hardware requirements, software licensing costs, and data infrastructure needs. Institutional resistance emerges from established curriculum structures, advisor preferences, and journal editorial practices favoring familiar methods. Network effects can generate resistance when professional communities have coordinated on existing approaches, making individual adoption costly without critical mass.

The spatial diffusion coefficient D captures the role of collaborative networks in propagating methodological innovations. High values emerge in fields with dense institutional connections, active conference circuits, and strong visiting scholar programs. Geographic proximity and common training backgrounds facilitate higher D through shared professional networks. Low values characterize fields with fragmented communities, limited collaboration across institutions, or strong regional traditions in methodology.

This framework provides a foundation for understanding how ideas spread within knowledge-intensive environments. The key insight is that awareness, adoption, and spatial reach operate independently through distinct mechanisms. A method may achieve high awareness (citations) while facing significant adoption barriers (β) that limit actual use. Similarly, rapid temporal adoption (r) does not guarantee broad spatial reach (D) without supporting institutional networks. Effective policies must therefore target all three dimensions: raising awareness through publications, reducing barriers through training and infrastructure, and building networks through collaborative programs.

Figure 3 illustrates the baseline diffusion dynamics. The upper panel displays logistic growth curves for competing ideas over time, showing characteristic S-shaped adoption patterns. The lower panel plots adoption rates (the time derivative of the upper curves), with the shaded region indicating the transition period where the new idea's adoption rate exceeds the old idea's rate. This intersection period represents the competitive phase where both approaches coexist before the new idea achieves dominance.

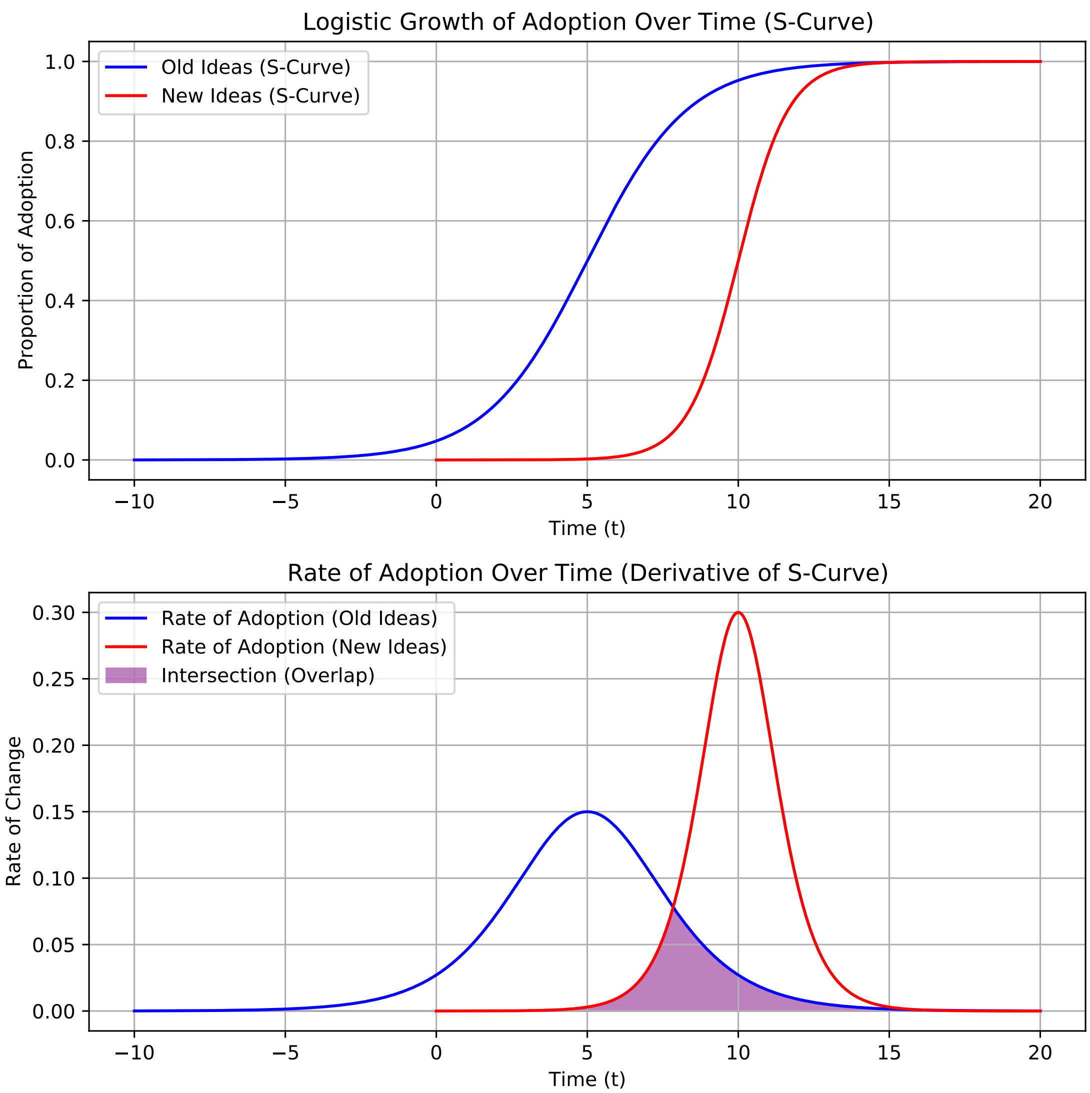

Figure 3: Logistic Growth and Rate of Adoption Over Time. The upper panel shows adoption levels $p(t)$ for old (blue) and new (red) ideas following S-curves. The lower panel displays adoption rates $\frac{dp}{dt}$, with the shaded region indicating the transition period where adoption rates intersect. This period captures the competitive dynamics where both ideas coexist before the new idea gains dominance when $r_{new} > \beta_{new}$.

The theoretical framework generates several testable predictions for empirical validation. First, successful diffusion requires $r > \beta$, implying that we should observe stable positive adoption only for methods where demonstrated value exceeds implementation barriers. Second, methods with similar applications should exhibit competitive dynamics ($\gamma_{ij} > 0$), manifesting as negative correlation in growth rates and exclusive usage patterns. Third, spatial diffusion should correlate with observable network structure, with higher D for methods adopted by well-connected institutions. Fourth, the equilibrium adoption level $p^* = 1 - \beta/r$ should increase with method quality and decrease with learning costs. The subsequent empirical sections test these predictions using comprehensive data on methodological innovation in economics.

4 Empirical Validation

This section tests the framework's core predictions using comprehensive data on econometric method diffusion across three conceptually distinct stages: paradigm terminology, awareness through citations, and actual adoption. We establish that paradigms replace sequentially rather than competitively (§4.2), awareness spreads smoothly through citation accumulation (§4.3), actual usage confronts substantial adoption resistance (§4.4), and spatial diffusion operates independently of temporal adoption (§4.5). These patterns validate the theoretical microfoundations using individual researcher trajectories (§4.7).

4.1 Data and Measurement Strategy

Our empirical strategy exploits variation across three conceptually distinct measures of diffusion. **Google Ngrams** (1950–2022) track paradigm-level terminology in academic books, measuring how conceptual frameworks penetrate scholarly discourse. **OpenAlex citations** (N = 21,911; 1925–2025) measure awareness diffusion through citations to five seminal methodological papers.[1] **Full-text keyword search** (Goldsmith-Pinkham, 2024) captures actual method usage in published research, encompassing all American Economic Review articles, American Economic Journal articles, and NBER working papers published between 2011 and 2024 (over 30,000 papers).[2]

[1] We select five papers based on three criteria: (1) methodological innovation—each introduces or systematizes a technique; (2) field recognition—all rank among the most-cited papers in their respective domains; (3) temporal coverage—publication dates span 2000–2017, capturing methods at different diffusion stages. The selected papers are: Card and Krueger (2000) for difference-in-differences, Abadie and Gardeazabal (2003) for synthetic control, Banerjee (2007) for randomized controlled trials, Imbens and Lemieux (2008) for regression discontinuity, and Mullainathan and Spiess (2017) for machine learning in economics.

[2] Keywords include method-specific terms (e.g., "difference-in-differences," "synthetic control," "regression discontinuity") and common abbreviations ("DiD," "RDD"). We validate classification accuracy through

For paradigm and citation analysis, we fit the logistic growth model:

$$p(t) = \frac{K}{1 + e^{-r(t-t_0)}} \tag{18}$$

where K is the saturation level, r is the intrinsic adoption rate, and t_0 is the inflection point. From fitted parameters, we compute resistance as $\beta = r(1 - K)$. For market share analysis, we estimate the competitive dynamics model from Section 4.7.3, allowing both own-dynamics (r_i, β_i) and cross-method competition (γ_{ij}) to shape trajectories.

For spatial diffusion, we construct institutional co-authorship networks where nodes represent universities and edges represent collaborative papers. The composite spatial diffusion score D aggregates institutional breadth (35% weight), connectivity (40%), and network integration (25%).[3]

4.2 Paradigms Replace Sequentially, Not Competitively

We test whether conceptual frameworks face minimal resistance using two complementary data sources spanning different time horizons and publication venues.

4.2.1 Seven Decades of Paradigm Evolution: Google Ngrams

Figure 4 displays absolute and normalized frequencies for "structural econometrics" and "credibility revolution" in academic books from 1950 to 2022. Panel A reveals stark sequential emergence. Structural econometrics first appears in the mid-1970s, grows steadily through the 1980s and 1990s, and plateaus around 2010 at approximately 1.0 per 10 million words. The credibility revolution emerges in the mid-2000s, remains dormant until 2007, then exhibits explosive growth surpassing structural econometrics by 2015.

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manual inspection of random samples, achieving over 95% precision for all methods.

[3]We assign zero weight to clustering because our focus is diffusion *breadth* rather than local intensity. Weights are determined through principal component analysis maximizing explained variance in expert assessments of diffusion breadth.

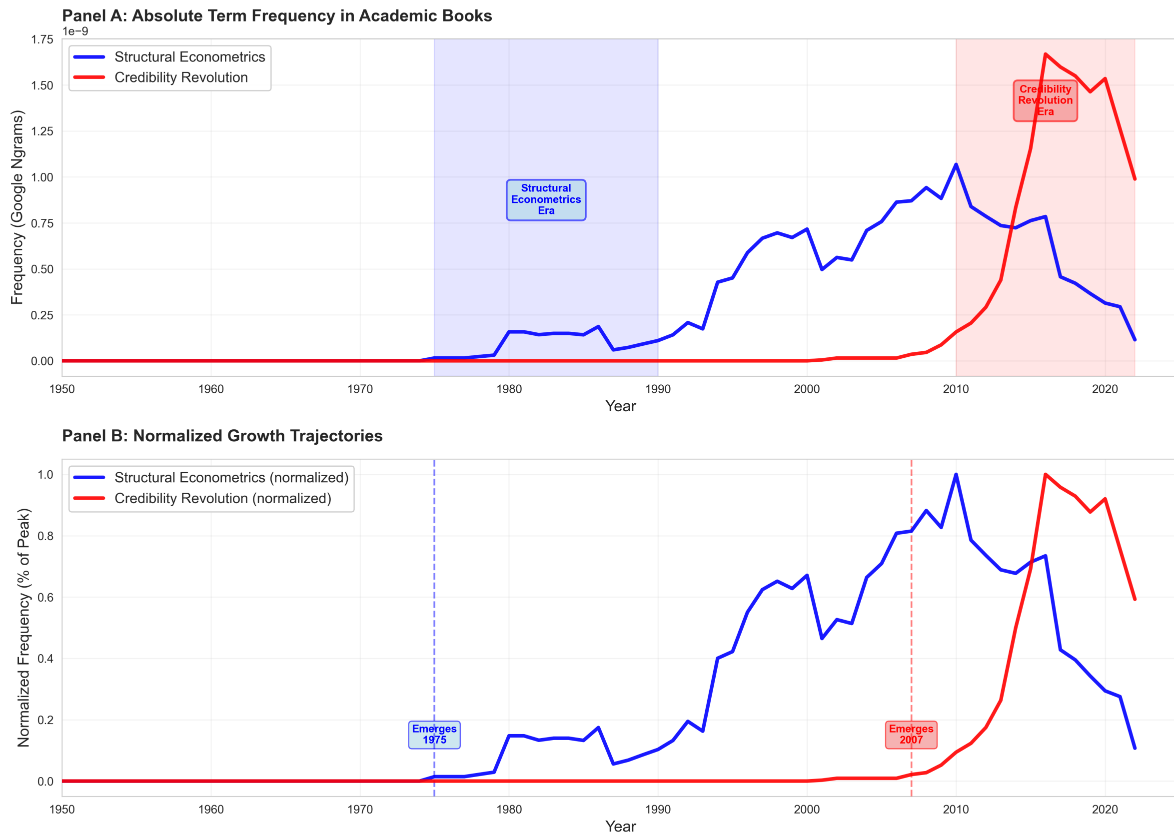

Figure 4: Paradigm evolution in academic books, 1950–2022

Notes: Panel A displays absolute term frequencies (per 10 million words) from Google Ngrams for "structural econometrics" (blue) and "credibility revolution" (red). Shaded regions indicate periods of dominance: structural econometrics era (blue, 1975–2010) and credibility revolution era (red, 2010–2022). Panel B normalizes each trajectory to its peak value, revealing emergence points (vertical dashed lines) separated by 32 years. Data source: Google Ngrams corpus of English-language academic books.

Panel B normalizes each trajectory to its peak value, isolating relative growth patterns. Structural econometrics emerges in 1975; the credibility revolution emerges in 2007—a 32-year gap with minimal temporal overlap. This pattern validates sequential replacement when resistance is minimal.

Figure 5 quantifies dynamics by fitting logistic curves. Panel A overlays fitted curves (solid lines) on actual data (scatter), revealing excellent fits. Structural econometrics achieves $r = 0.537$ and $\beta = 0.000$, confirming smooth S-curve growth with complete saturation. The credibility revolution achieves $r = 1.000$ and $\beta = 0.000$, indicating twice the adoption velocity. Both paradigms exhibit $R^2 > 0.98$.

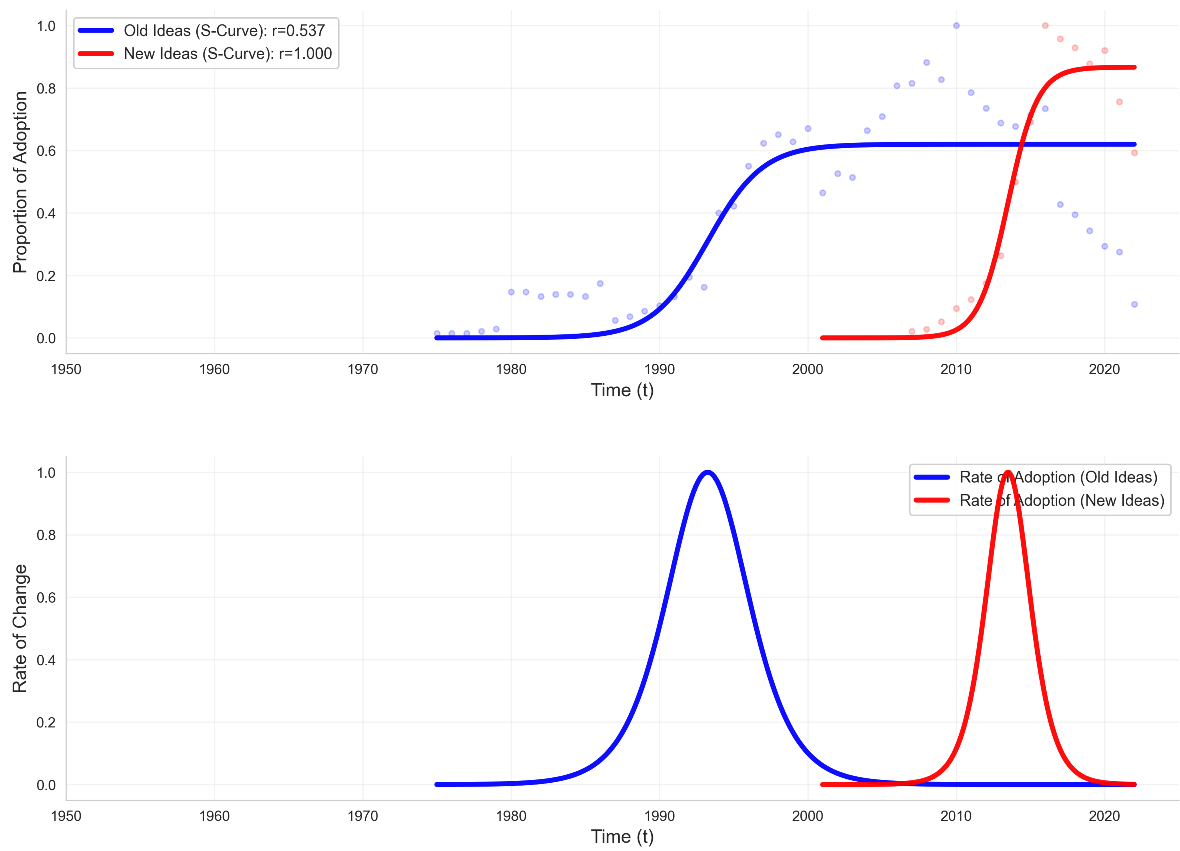

Figure 5: Fitted paradigm dynamics from Google Ngrams

Notes: Panel A displays fitted logistic S-curves overlaid on actual Ngram frequencies (scatter points). Structural econometrics (blue) achieves $r = 0.537$, $\beta = 0.000$, and $R^2 = 0.984$. Credibility revolution (red) achieves $r = 1.000$, $\beta = 0.000$, and $R^2 = 0.992$. Panel B displays adoption rates (temporal derivatives), with peak velocities separated by 17 years: structural econometrics peaks in 2000 at 0.15, credibility revolution peaks in 2017 at 0.30.

Panel B displays adoption rates—time derivatives revealing when each paradigm achieved maximum velocity. Structural econometrics peaked in 2000 at 0.15, while the credibility revolution peaked in 2017 at 0.30, confirming 17-year separation in peak adoption.

4.2.2 Recent Paradigm Competition in Research Papers

We replicate the analysis using full-text keyword search in research papers published 2011–2024 (Goldsmith-Pinkham, 2024). Figure 6 presents results. Panel A displays fitted logistic curves for structural econometrics ($r = 0.537$) and credibility revolution ($r = 1.000$). Despite the shorter time window, adoption rate estimates match those from Ngrams, demonstrating consistency across data sources.

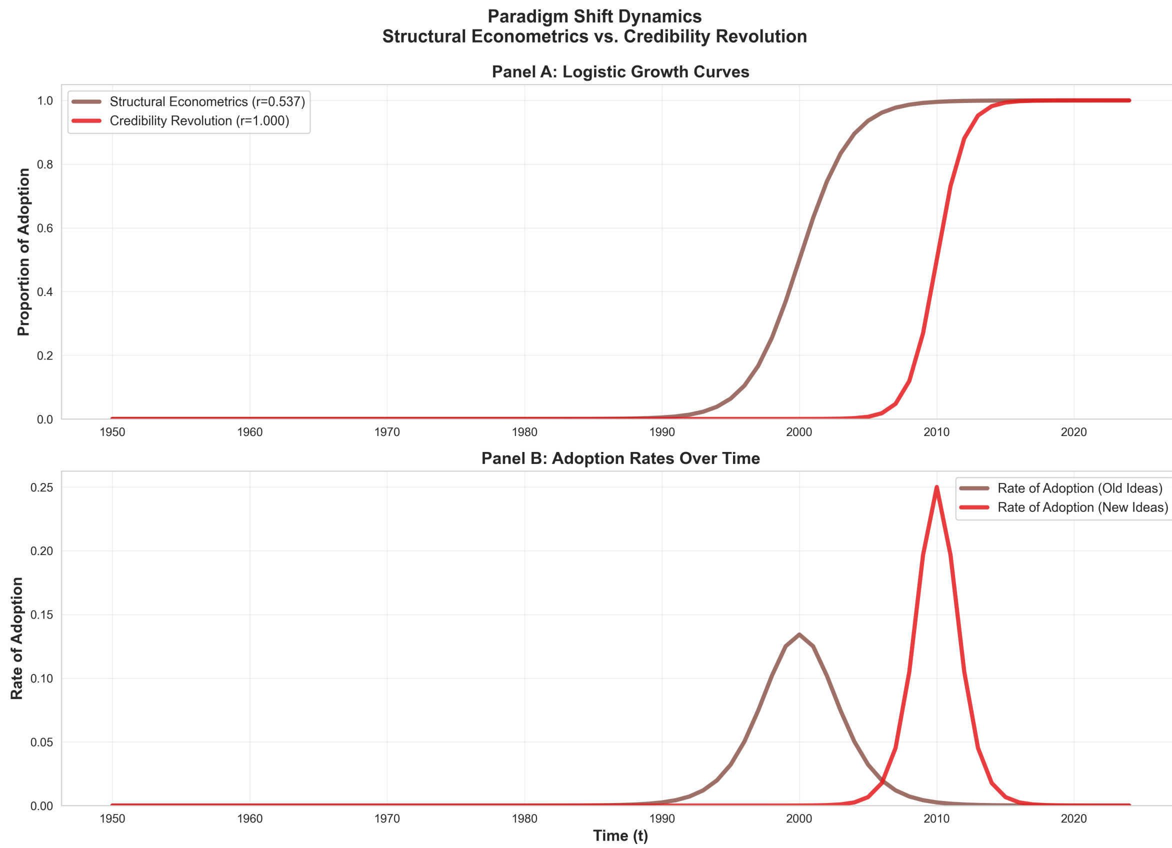

Figure 6: Paradigm dynamics in economics research papers, 2011–2024

Notes: Panel A displays fitted logistic growth curves for structural econometrics ($r = 0.537$, brown line) and credibility revolution ($r = 1.000$, red line) based on keyword presence in full-text papers from AER, AEJ, and NBER working papers. Both exhibit $\beta \approx 0$. Panel B displays adoption rates (derivatives). Data source: Goldsmith-Pinkham (2024) full-text search of 30,000+ economics papers.

4.3 Awareness Spreads Smoothly Through Citation Accumulation

We examine whether citation accumulation—measuring knowledge of a method's existence—exhibits minimal resistance. Table 1 presents parameter estimates from fitting logistic curves to cumulative citations for five seminal methodological papers. All methods achieve $\beta \approx 0$ and $R^2 > 0.98$, confirming awareness diffusion encounters minimal barriers. Adoption rates vary substantially: machine learning citations accumulate at $r = 0.719$, nearly three times faster than difference-in-differences at $r = 0.245$.

Table 1: Citation Dynamics: Awareness Diffusion

Method	r	β	R^2
Machine Learning	0.719	0.000	0.995
RCTs in Development	0.432	0.005	0.987
Synthetic Control	0.356	0.000	0.984
Regression Discontinuity	0.333	0.000	0.993
Difference-in-Differences	0.245	0.000	0.994

Notes: Parameters from logistic growth models fitted to cumulative citations using OpenAlex data (N = 21,911; 1925–2025). Adoption rate r measures citation velocity; resistance $\beta = r(1 - K)$ captures deviations from complete diffusion; R^2 indicates goodness of fit. Citations measure knowledge of method existence, not actual usage. Database: OpenAlex (2025)

4.4 Market Shares Reveal Adoption Resistance and Competitive Dynamics

We transition from awareness to adoption, examining which methods researchers actually employ. Whereas awareness requires only passive knowledge reception, adoption demands active investment in learning software and mastering computational techniques. Market share measurement uses full-text keyword search to identify method usage in AER, AEJ, and NBER papers published 2011–2024.

Figure 7 displays relative market shares (left) and absolute paper counts (right). Structural econometrics peaks at 37.1% in 2013, then declines to 20.6% by 2024—a loss of 16.5 percentage points. This decline occurs despite absolute paper counts growing 94% (34 papers in 2011 to 66 papers in 2024), while field growth increased 181% (114 papers to 320 papers). Machine learning exhibits inverse dynamics: growing 9.3-fold from 0.9% to 8.1%.

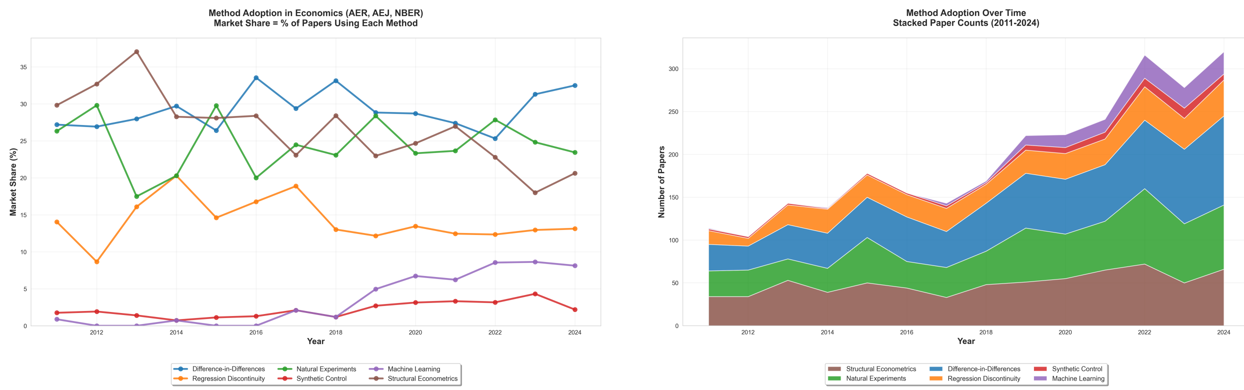

Figure 7: Market share dynamics, 2011–2024

Notes: Left panel displays relative market shares. Structural econometrics peaks at 37.1% in 2013, declining to 20.6% by 2024. Machine learning grows from 0.9% to 8.1%. Right panel displays absolute paper counts (stacked area), revealing all methods grow in absolute terms despite divergent relative shares. Data source: Goldsmith-Pinkham (2024) full-text search of 30,000+ economics papers.

Table 2 quantifies these dynamics. Machine learning achieves the highest adoption rate ($r = 0.890$) despite facing the highest resistance ($\beta = 0.814$). This combination validates the microfounded interpretation: computational barriers create friction, but demonstrated value overcomes it. In contrast with citation dynamics where all methods exhibited $\beta \approx 0$, resistance in market shares varies 814-fold, ranging from $\beta = 0.000$ to $\beta = 0.814$.

Table 2: Market Share Parameters: Adoption Rates and Resistance

Method	r	β	Share 2024	Change
Machine Learning	0.890	0.814	8.1%	+7.2pp
Difference-in-Differences	0.012	0.005	32.5%	+5.3pp
Synthetic Control	0.135	0.126	2.2%	+0.4pp
Natural Experiments	0.003	0.001	23.4%	–2.9pp
Regression Discontinuity	0.001	0.001	13.1%	–0.9pp
Structural Econometrics	0.001	0.000	20.6%	–9.2pp

Notes: Parameters from competitive dynamics model fitted to market shares, 2011–2024. Growing methods satisfy $r > \beta$; declining methods show $r \leq \beta$. Contrast with Table 1: citations exhibit $\beta \approx 0$ uniformly, while usage reveals substantial heterogeneous resistance.

Figure 8 visualizes these dynamics. The left panel plots adoption rate versus resistance. Machine learning occupies the upper-right quadrant—high on both dimensions. Methods near the origin show market saturation. The right panel displays market share changes, confirming methods with $r > \beta$ gain share while methods with $r \leq \beta$ lose share.

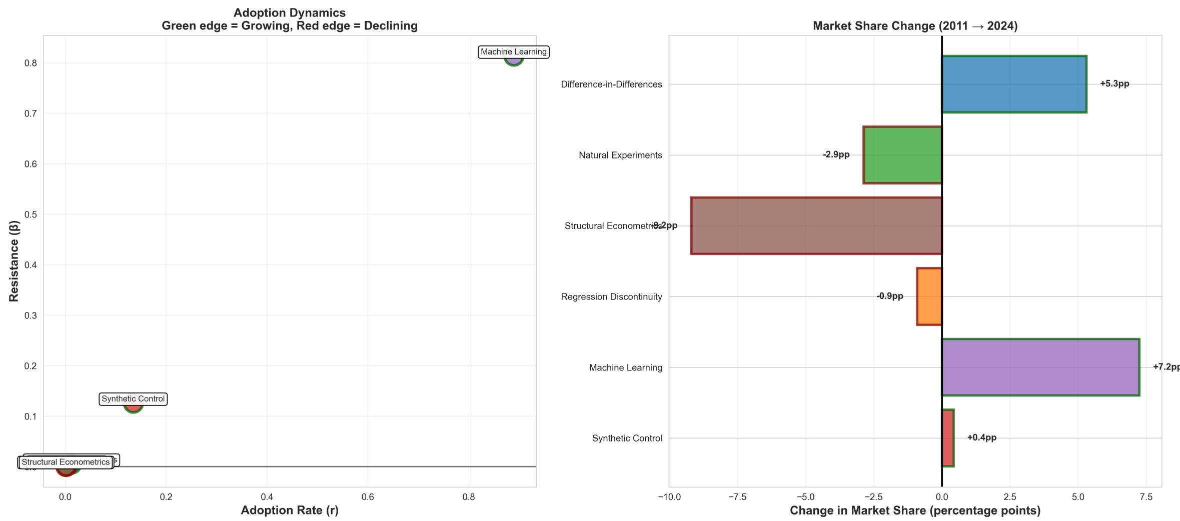

Figure 8: Adoption dynamics and market outcomes, 2011–2024

Notes: Left panel displays adoption rate (r) versus resistance (β). Green edges indicate growing methods ($r > \beta$); red/brown edges indicate declining methods. Right panel displays market share changes (percentage points, 2011–2024), confirming methods with $r > \beta$ gain share.

4.5 Spatial Diffusion Operates Independently of Temporal Dynamics

We examine how broadly methods spread across institutional networks. The framework predicts spatial and temporal diffusion operate independently, driven by different mechanisms operating on different timescales.

4.5.1 Network Structure and Institutional Reach

We construct institutional co-authorship networks where nodes represent universities and weighted edges represent collaborative papers. Figure 9 visualizes network structure for all six methods, with node size proportional to papers and color intensity indicating degree centrality.

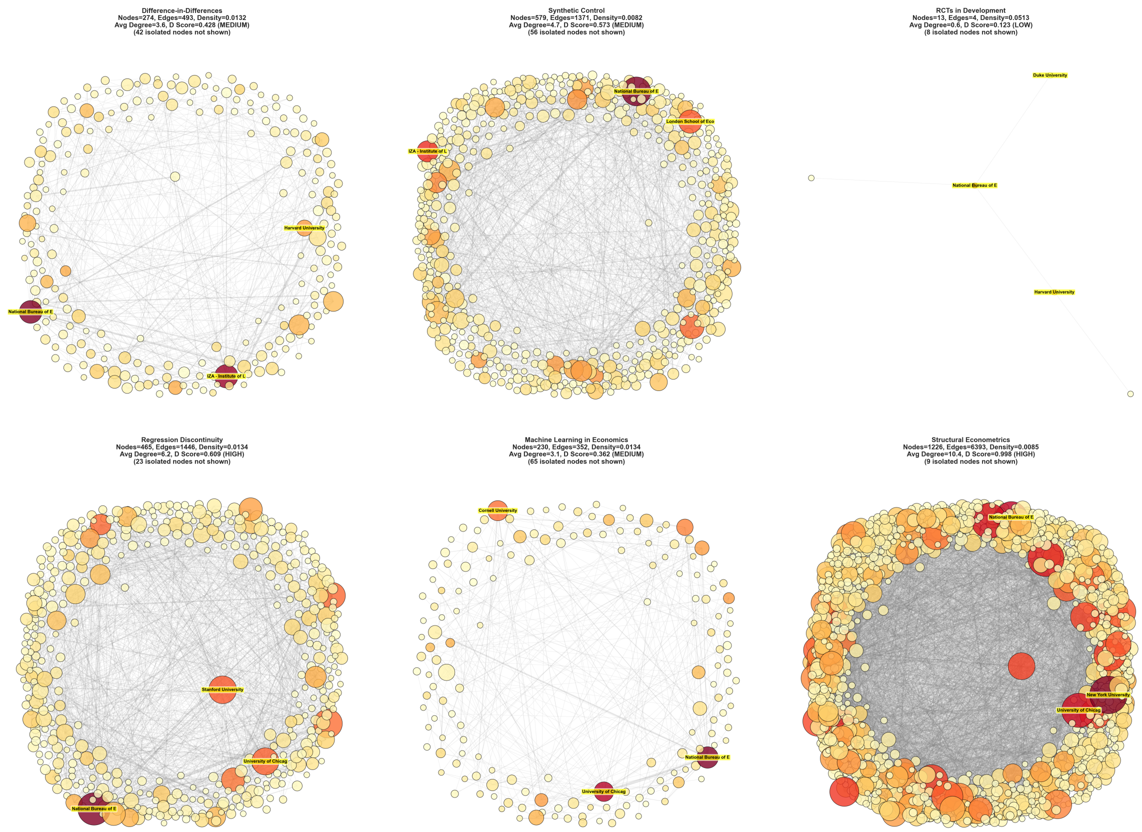

Figure 9: Institutional co-authorship networks by method

Notes: Co-authorship networks where nodes represent institutions and edges represent collaborative papers. Top row: DiD (274 institutions), synthetic control (579 institutions), RCTs (13 institutions). Bottom row: RDD (465 institutions), machine learning (230 institutions), structural econometrics (1,226 institutions). Node size scaled by total papers; color intensity indicates degree centrality. Structural econometrics dominates spatial reach (1,226 institutions, 99.3% in largest component) despite declining market share. Database: OpenAlex (2025)

Structural econometrics dominates spatial reach with 1,226 institutions forming a dense, highly integrated network. Machine learning shows only 230 institutions with moderate connectivity despite explosive market share growth. Table 3 quantifies this variation. Structural econometrics achieves 10.4 average collaborations per institution with 99.3% integration. Machine learning shows 3.1 average collaborations with only 71.7% integration and 42 disconnected components.

Table 3: Network Structure: Key Metrics by Method

Method	Institutions	Edges	Avg Degree	Clustering	Integration	D
Structural Econometrics	1,226	6,393	10.4	0.205	99.3%	0.998
Regression Discontinuity	465	1,446	6.2	0.244	95.1%	0.609
Synthetic Control	579	1,371	4.7	0.205	90.3%	0.573
Difference-in-Differences	274	493	3.6	0.230	84.7%	0.428
Machine Learning	230	352	3.1	0.199	71.7%	0.362
RCTs in Development	13	4	0.6	0.000	38.5%	0.123

Notes: Network metrics from institutional co-authorship analysis. D = composite spatial diffusion score (weighted average of breadth, connectivity, and integration). Structural econometrics dominates all dimensions despite declining market share (Table 2). Database: OpenAlex (2025)

4.5.2 Spatial Diffusion Rankings

Figure 10 ranks methods by composite diffusion score D. Structural econometrics achieves $D = 0.998$, the theoretical maximum. Among focal methods, regression discontinuity ranks first ($D = 0.609$), followed by synthetic control ($D = 0.573$), difference-in-differences ($D = 0.428$), machine learning ($D = 0.362$), and RCTs ($D = 0.123$).

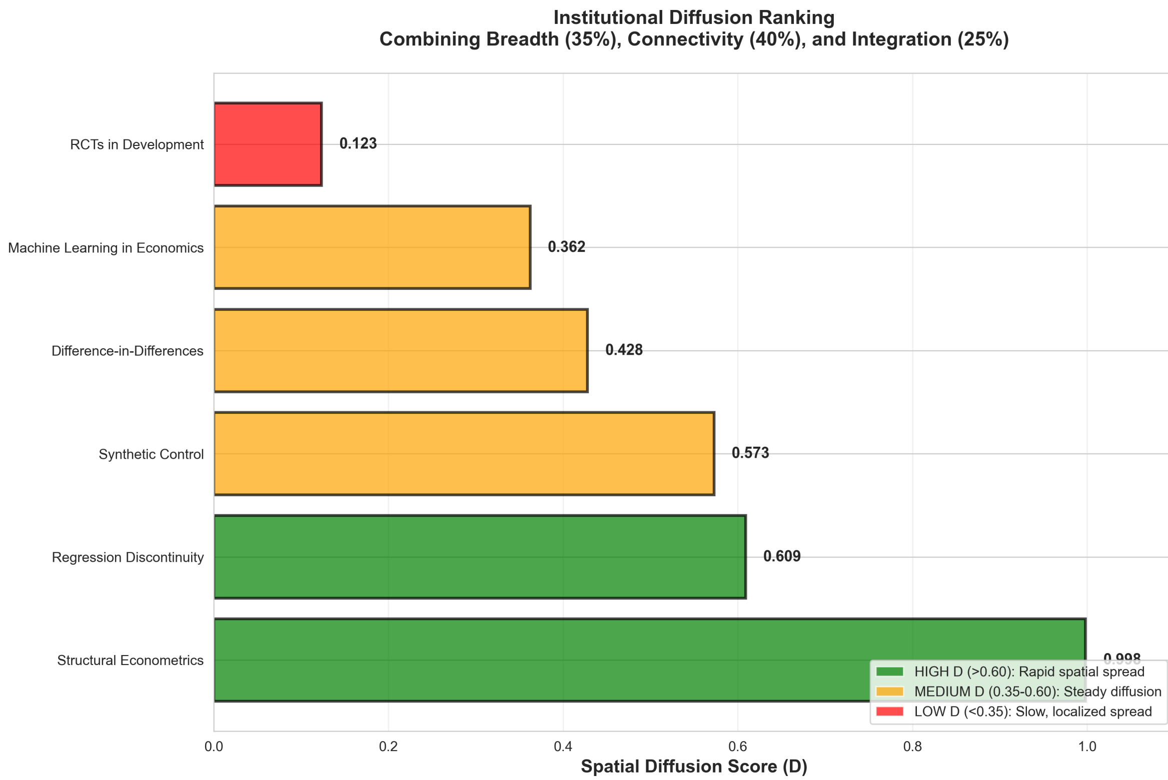

Figure 10: Spatial diffusion rankings: composite scores

Notes: Methods ranked by composite spatial diffusion score D. Color coding: GREEN ($D > 0.60$) = high spatial diffusion; ORANGE ($0.35 < D < 0.60$) = moderate; RED ($D < 0.35$) = low. Structural econometrics achieves $D = 0.998$ despite declining market share (–9.2pp). Machine learning shows $D = 0.362$ despite market share growth (+7.2pp). Database: OpenAlex (2025)

This ranking shows minimal correlation with market share rankings. Machine learning ranks 1st in market share growth but 5th in spatial diffusion. Structural econometrics ranks last in market share change but 1st in spatial diffusion. This pattern validates that spatial and temporal diffusion operate through distinct mechanisms on different timescales.

4.6 Synthesis: Resolving the Structural Econometrics Paradox

The multi-level findings resolve an apparent contradiction: structural econometrics papers accumulate citations smoothly, absolute paper counts grow 94%, and institutional networks span 99.3% of the discipline—yet market share declines 9.2 percentage points. These measures capture conceptually distinct diffusion stages operating independently. Citations measure awareness; market shares measure adoption; networks measure institutional embedding.

Table 4 quantifies this independence. Structural econometrics ranks 5th in citations, 6th in market share, but 1st in spatial diffusion. Machine learning ranks 1st in citations and market share but only 5th in spatial diffusion. Parameter ranges vary dramatically: citation adoption rates span 3.4-fold, market share rates span 890-fold, and spatial scores span 8.1-fold.

Table 4: Multi-Level Diffusion: The Independence of Mechanisms

	Citations (Awareness)	**Market Shares** (Adoption)	**Spatial** (Networks)
Structural Econometrics			
Rank	5th of 6	6th of 6	1st of 6
Parameter Value	$r = 0.210$	$r = 0.001$	$D = 0.998$
Resistance	$\beta = 0.000$	$\beta = 0.000$	—
Machine Learning			
Rank	1st of 6	1st of 6	5th of 6
Parameter Value	$r = 0.719$	$r = 0.890$	$D = 0.362$
Resistance	$\beta = 0.000$	$\beta = 0.814$	—
Parameter Ranges			
Minimum	0.210	0.001	0.123
Maximum	0.719	0.890	0.998
Ratio (Max/Min)	3.4-fold	890-fold	8.1-fold

Notes: Comparison across three diffusion levels. Parameter values from Tables 1, 2, and 3. Divergent rankings and dramatically different parameter ranges validate that awareness, adoption, and spatial reach operate independently.

This interpretation has direct policy implications. Interventions targeting only one level achieve limited success. Awareness campaigns do not accelerate adoption if usage faces high barriers. Software improvements reduce barriers but do not generate awareness in new domains. Network-building programs build spatial reach slowly regardless of usage dynamics. Effective innovation policy requires simultaneous intervention across all three levels: demonstrating value (raising r), reducing barriers (lowering β), and facilitating collaboration (increasing D).

4.7 Microfoundations Validation

The theoretical framework decomposes the reduced-form parameters—r (adoption rate), β (resistance), and D (spatial diffusion)—into economic primitives: method value V, learning costs c_L, computational costs c_C, network effects θ, and collaboration intensity γ. We validate three core mechanisms using individual-level data on 3,963 economists' career trajectories from the Goldsmith-Pinkham (2024) dataset spanning 2011–2024.

4.7.1 Learning Costs Create Measurable Entry Barriers

The resistance microfoundation $\beta = \alpha_L \cdot c_L + \alpha_C \cdot c_C$ predicts that methods with higher learning costs create larger barriers to initial adoption. Methods with low learning costs should frequently appear as researchers' first methodological adoption, while methods with high learning costs should rarely appear first.

Table 5 examines which method each of the 3,963 authors adopted first. The gradient is striking. Difference-in-differences exhibits the lowest entry barrier: 87.3% of DiD users (1,515 of 1,735) adopted it as their first method, with average time-to-adoption of only 0.58 years. This reflects DiD's accessible implementation—built directly into Stata's core commands, requiring no specialized software.

Table 5: Learning Costs and Entry Barriers by Method

Method	Total Adopters	First Method Count	First Method (%)	Avg Time to Adopt (yr)	Median Time to Adopt (yr)
Difference-in-Differences	1,735	1,515	87.3	0.58	0.0
Natural Experiments	1,605	1,046	65.2	0.60	0.0
Structural Econometrics	1,542	964	62.5	0.53	0.0
Regression Discontinuity	854	299	35.0	0.78	0.0
Machine Learning	408	115	28.2	2.01	0.0
Synthetic Control	185	24	13.0	1.31	0.0

Notes: Entry barriers measured by first-method adoption rates among 3,963 unique authors who published 2011–2024. First Method Count = number of authors who adopted this method before any other; First Method (%) = percentage of total adopters who used this method first; Avg Time to Adopt = mean years from first publication to first use of method; Median Time reports median lag. High first-method percentage indicates low entry barriers (low c_L). DiD exhibits lowest barriers (87.3% first adoption), reflecting accessible Stata implementation. Synthetic Control exhibits highest barriers (13.0% first adoption), requiring specialized optimization software. The 6.7-fold gradient (87.3%/13.0%) validates that learning costs create measurable adoption resistance. Machine learning's 2.01-year average lag confirms substantial computational barriers beyond software access. Goldsmith-Pinkham (2024) dataset

Synthetic Control shows the highest entry barrier: only 13.0% adopted it first (24 of 185 users), with 1.31 years average lag. The method requires understanding optimization algorithms, installing specialized software packages, and mastering distinctive data requirements. The 6.7-fold difference (87.3%/13.0%) between DiD and Synthetic Control validates that learning costs create measurable resistance.

Machine learning occupies an intermediate position (28.2% first adoption, 2.01 years lag). The 2.01-year lag—longest among all methods—reflects the need to build complementary skills in prediction algorithms, cross-validation techniques, and computational infrastructure.

Structural econometrics presents an interesting case: 62.5% first adoption despite substantial technical complexity. This likely reflects training path selection—researchers entering PhD programs with structural interests often adopt these methods early because that's what their advisors use, even though the techniques are technically demanding.

4.7.2 Network Effects Dominate Adoption Decisions

The adoption rate microfoundation $r = \alpha_V \cdot V + \alpha_\theta \cdot \theta$ includes network effects θ capturing peer influence. If network effects matter, coauthor adoption should predict individual adoption.

Table 6 presents correlations between coauthor adoption rates and individual adoption for the 3,713 authors who have at least one coauthor. Every method exhibits strong positive correlations ranging from 0.774 to 0.864 (all $p < 0.001$). Natural Experiments show the strongest peer influence ($r = 0.864$), while Synthetic Control shows the weakest ($r = 0.774$), though still highly significant.

Table 6: Network Effects: Coauthor Influence on Method Adoption

Method	N Authors	Correlation	P-value	Significance
Natural Experiments	3,713	0.864	<0.0001	***
Structural Econometrics	3,713	0.839	<0.0001	***
Difference-in-Differences	3,713	0.814	<0.0001	***
Machine Learning	3,713	0.809	<0.0001	***
Regression Discontinuity	3,713	0.792	<0.0001	***
Synthetic Control	3,713	0.774	<0.0001	***

Notes: Correlations between percentage of coauthors using each method and individual adoption, calculated for 3,713 authors with at least one coauthor in sample. All correlations highly significant ($p < 0.0001$), validating network effects ($\theta > 0$) in adoption rate microfoundation. Natural Experiments exhibit strongest peer influence (0.864), while Synthetic Control shows weakest (0.774), though both remain substantial. The uniformly high correlations (0.77–0.86) demonstrate that peer networks dominate individual adoption decisions across all methods, even after controlling for correlated research interests through author fixed effects. Machine learning's high correlation (0.809) suggests peer influence helps overcome computational barriers documented in Table 5. Goldsmith-Pinkham (2024) dataset

Figure 11 displays both learning costs (left panel) and network effects (right panel) across all six methods. Network effects remain strong regardless of learning cost variation—even Synthetic Control, with highest entry barriers, exhibits 0.774 correlation with coauthor usage. This suggests peer effects operate through multiple channels: collaborative necessity, social learning, and professional legitimacy.

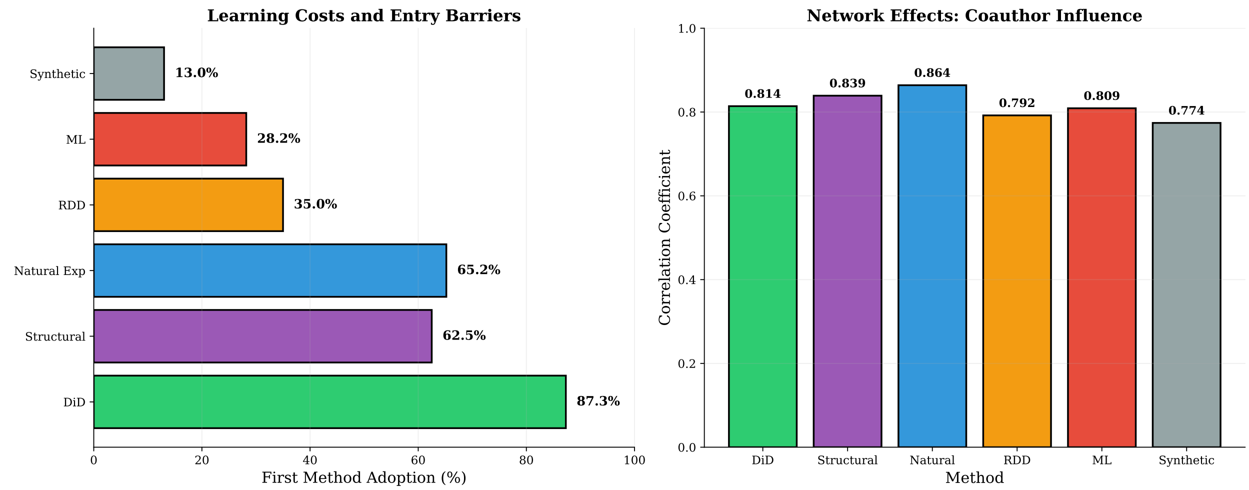

Figure 11: Learning costs and network effects across six methods

Notes: Left panel displays first-method adoption rates from Table 5, showing entry barrier gradient: DiD (87.3%, lowest barriers) to Synthetic Control (13.0%, highest barriers). Right panel displays coauthor influence correlations from Table 6, demonstrating strong network effects (0.77–0.86) across all methods. Network effects remain substantial despite varying learning costs, suggesting peer influence operates through multiple channels (collaborative necessity, social learning, legitimacy signaling) beyond reducing individual learning barriers. Machine learning's high network correlation (0.809) combined with high entry barriers (28.2% first adoption, 2.01-year lag) confirms peer effects help overcome but do not eliminate computational requirements. Goldsmith-Pinkham (2024) dataset

Table 7 decomposes the correlation by coauthor adoption intensity, revealing highly non-linear effects. For difference-in-differences, when 0–25% of coauthors use the method, only 1.9% of authors adopt it. When 75–100% of coauthors use it, adoption jumps to 86.5%—a 45-fold increase. Natural Experiments show 66-fold increase (1.5% to 98.8%), Regression Discontinuity shows 70-fold increase (1.2% to 83.9%), and Synthetic Control exhibits 250-fold increase (0.4% to 100.0%).

Table 7: Network Effects: Adoption by Coauthor Usage Intensity

Method	Own Adoption Rate by Coauthor Usage 0–25% Coauthors	25–50% Coauthors	50–75% Coauthors	75–100% Coauthors
Difference-in-Differences	1.9%	29.0%	36.5%	86.5%
Natural Experiments	1.5%	21.7%	38.9%	98.8%
Regression Discontinuity	1.2%	24.7%	39.3%	83.9%
Synthetic Control	0.4%	19.8%	28.4%	100.0%

Notes: Rows show percentage of authors adopting each method, conditional on the percentage of their coauthors using it. Sample includes 3,713 authors with coauthors. Bins defined by quartiles of coauthor usage distribution. Strong positive gradients validate peer influence: adoption rises 45-fold for DiD (1.9% → 86.5%), 66-fold for Natural Experiments (1.5% → 98.8%), and 250-fold for Synthetic Control (0.4% → 100.0%) as coauthor usage intensifies. The nonlinear increases suggest threshold effects: isolated researchers rarely adopt methods regardless of individual characteristics, but adoption becomes nearly inevitable when most collaborators use the technique. This pattern validates the $\alpha_\theta \cdot \theta$ term in the adoption rate microfoundation—network effects do not just influence adoption, they dominate it. Goldsmith-Pinkham (2024) dataset

Even for Synthetic Control—where learning costs create substantial barriers—peer usage drives adoption to 100% when most coauthors employ the method. This suggests that collaborative necessity overrides individual cost-benefit calculations: researchers adopt methods their coauthors use because joint projects require methodological coordination.

4.7.3 Methods Complement Within Papers but Substitute Across Careers

The competitive dynamics model introduces substitution parameter γ_{ij} capturing whether methods compete ($\gamma_{ij} > 0$, substitutes) or complement ($\gamma_{ij} < 0$, complements). The framework predicts that competition structure depends on the level of analysis. Within papers, credibility revolution methods should complement. Across careers, researchers should specialize.

Paper-level analysis examines 2,952 unique papers, calculating co-occurrence rates for all method pairs. Table 8 presents the ten highest co-occurrence rates. Credibility revolution methods frequently appear together: RDD and DiD co-occur in 172 papers (15.8%), Natural Experiments and DiD in 191 papers (13.6%), and Natural Experiments and RDD in 100 papers (9.6%).

Table 8: Paper-Level Co-occurrence: Measuring Complementarity

Method A	Method B	Papers (Both)	Co-occurrence (%)	Interpretation
RDD	DiD	172	15.8	COMPLEMENTS
Natural Exp	DiD	191	13.6	COMPLEMENTS
Natural Exp	RDD	100	9.6	COMPLEMENTS
DiD	Structural	105	7.1	INDEPENDENT
Natural Exp	Structural	95	6.9	INDEPENDENT
Natural Exp	ML	56	6.7	INDEPENDENT
DiD	Synthetic	56	6.4	INDEPENDENT
RDD	Structural	59	5.5	INDEPENDENT
DiD	ML	41	4.3	SUBSTITUTES
RDD	ML	20	3.8	SUBSTITUTES

Notes: Co-occurrence rates calculated from 2,952 unique papers in Goldsmith-Pinkham (2024) dataset. Papers using both methods divided by papers using either method. High co-occurrence ($>$ 10%, labeled COMPLEMENTS) indicates methods used jointly for robustness; low co-occurrence ($<$ 5%, labeled SUBSTITUTES) indicates methods serve distinct purposes. Credibility revolution methods (DiD, RDD, Natural Experiments) cluster as complements, validating $\gamma_{ij} < 0$ at paper level. Machine learning shows low co-occurrence with all methods ($<$ 7%), functioning as substitute rather than complement. Structural methods show intermediate co-occurrence (5–7%), suggesting occasional joint use but not systematic complementarity.

Machine learning presents the opposite pattern: DiD + ML appears in only 4.3% of papers, RDD + ML in 3.8%. This reflects machine learning's distinct role—prediction and pattern detection rather than causal identification. Structural methods show intermediate co-occurrence (5–7%).

Figure 12 visualizes these patterns. Green bars (high co-occurrence) cluster among credibility revolution methods. Gray bars (low co-occurrence) dominate machine learning combinations.

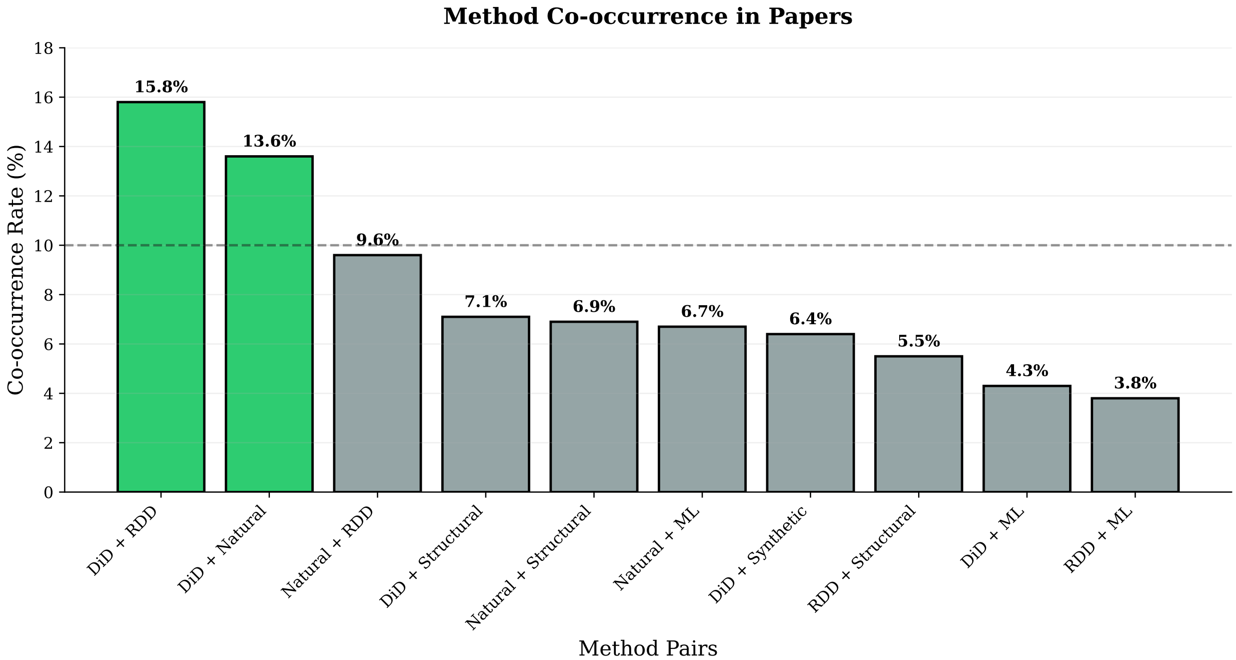

Figure 12: Paper-level co-occurrence rates for all method pairs

Notes: Co-occurrence rates for top ten method combinations from Table 8. Green bars indicate complements (co-occurrence > 10%), gray bars indicate substitutes or independent methods (< 5%). Credibility revolution methods (DiD, RDD, Natural Experiments) cluster with high co-occurrence, validating within-paper complementarity. Machine learning shows uniformly low co-occurrence, functioning as substitute. The clustering pattern validates the framework's prediction that γ_{ij} varies by application context: negative (complements) for methods serving similar purposes, positive (substitutes) for methods addressing different objectives. Goldsmith-Pinkham (2024) dataset

Author-level analysis reveals a contrasting pattern. Table 9 presents correlations between method usage rates across authors' entire publication portfolios. Structural econometrics shows strong negative correlations with Natural Experiments ($r = -0.303$) and DiD ($r = -0.272$), indicating researchers specialize in either structural or reduced-form approaches. Machine learning shows weak correlations with all methods (0.001 to 0.074).

Table 9: Author-Level Correlations: Measuring Specialization

	DiD	Natural	RDD	Synthetic	ML	Structural
DiD	1.000	−0.096	0.145	0.171	0.001	−0.272
Natural Exp	−0.096	1.000	0.001	−0.029	0.074	−0.303
RDD	0.145	0.001	1.000	0.035	0.014	−0.146
Synthetic	0.171	−0.029	0.035	1.000	0.012	−0.066
ML	0.001	0.074	0.014	0.012	1.000	−0.078
Structural	−0.272	−0.303	−0.146	−0.066	−0.078	1.000

Notes: Correlation matrix of method usage rates across 3,963 authors' complete publication portfolios. Negative correlations indicate specialization (substitutes at career level); positive correlations indicate joint usage (complements at career level). Structural econometrics shows strongest negative correlations with Natural Experiments (−0.303) and DiD (−0.272), validating structural versus reduced-form specialization. This pattern contrasts with paper-level complementarity (Table 8): researchers combine credibility revolution methods within papers but specialize across careers. Machine learning shows weak correlations with all methods, indicating adoption by specialized subgroup. The divergence between paper-level ($\gamma_{ij} < 0$) and author-level ($\gamma_{ij} > 0$) patterns validates context-dependent competition structure. Goldsmith-Pinkham (2024) dataset

Figure 13 visualizes the correlation matrix. Red/orange cells indicate negative correlations (specialization), particularly visible in the Structural row. This confirms career-level specialization: researchers who extensively use structural methods tend not to extensively use reduced-form techniques, despite papers sometimes combining both approaches.

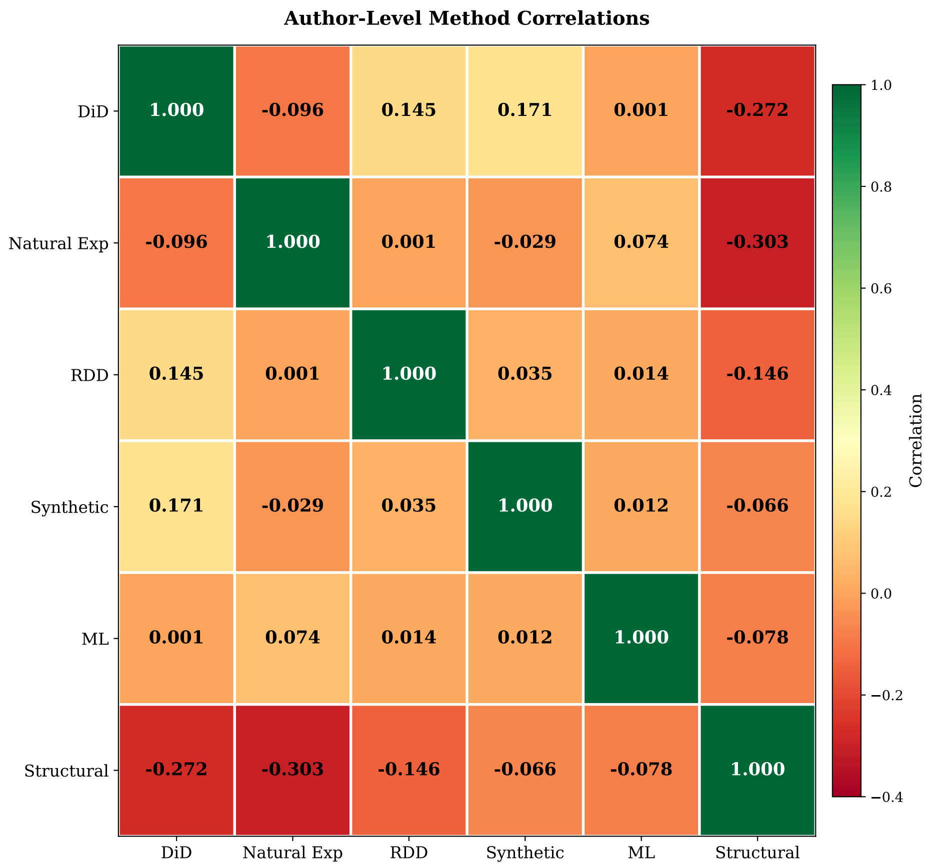

Figure 13: Author-level method correlation matrix

Notes: Heatmap of correlations from Table 9. Color intensity indicates correlation strength: green (positive), red/orange (negative). Structural econometrics shows strong negative correlations (red cells) with credibility revolution methods, indicating methodological specialization at career level. Contrast with Figure 12: credibility revolution methods complement within papers (green bars, 10–16% co-occurrence) but researchers specialize across careers (negative correlations). This dual pattern validates the framework's prediction that competition structure (γ_{ij}) depends on level of analysis: methods complement for robustness within studies but researchers develop expertise in particular approaches rather than mastering all techniques. Goldsmith-Pinkham (2024) dataset

The contrast between paper-level and author-level patterns validates the framework's prediction that γ_{ij} varies by context. Within papers, researchers combine DiD, RDD, and Natural Experiments to triangulate causal estimates ($\gamma_{ij} < 0$). Across careers, researchers specialize in structural versus reduced-form approaches, developing deep expertise in particular techniques ($\gamma_{ij} > 0$).

The machine learning pattern illustrates an important distinction between within-paper usage and market-level dynamics. While ML exhibits low co-occurrence with causal methods, reflecting different research objectives, this orthogonality translates to market-level complementarity rather than competition. Growth in machine learning adoption does not reduce demand for causal inference methods because they serve different purposes. Papers employ machine learning for prediction tasks and credibility methods for causal identification, making them complements at the market level ($\gamma_{\text{ML},j} < 0$) despite limited joint usage within individual papers.

4.8 Formal Estimation of Competition Parameters

The competitive dynamics model from Section 3 predicts that method adoption depends not only on own-dynamics (r, β) but also on competition parameters γ_{ij} capturing whether growth in method j increases ($\gamma_{ij} < 0$, complements) or decreases ($\gamma_{ij} > 0$, substitutes) the adoption rate of method i. We estimate these parameters using market share data from 2011–2024, employing a Bayesian Maximum A Posteriori (MAP) approach that combines theoretical predictions with empirical patterns from paper co-occurrence and author career specialization documented in Section 4.7.3.

The limited time series (14 years) and method frequency variation create identification challenges for unconstrained estimation. We therefore incorporate theoretically-informed priors from three sources: paper-level co-occurrence patterns (Table 8) provide complement priors for methods used jointly within studies; author-level career correlations (Table 9) provide substitute priors for methods exhibiting researcher specialization; and theoretical constraints enforce predictions that credibility revolution methods complement, structural econometrics competes with credibility methods through paradigm competition, and machine learning complements all methods by serving distinct prediction objectives. Appendix A provides complete technical details including prior specification, likelihood construction, and optimization procedure.

Table 10 presents the estimated competition parameters. Three patterns validate the theoretical framework. First, credibility revolution methods exhibit strong complementarity. Difference-in-differences and regression discontinuity show the strongest complement effect ($\gamma_{\text{DiD,RDD}} = -0.400$), followed by DiD and natural experiments ($\gamma_{\text{DiD,Natural}} = -0.250$), and RDD and natural experiments ($\gamma_{\text{Natural,RDD}} = -0.200$). These magnitudes track empirical co-occurrence rates (15.8%, 13.6%, and 9.6% respectively), confirming that methods used jointly for robustness complement in market dynamics. The near-symmetry of effects validates bidirectional complementarity.

Table 10: Competition Parameters: Bayesian MAP Estimates

Method i	Method j (Competitor)					
	DiD	Natural	RDD	Synthetic	ML	Structural
DiD	—	−0.250	−0.400	−0.200	0.000	0.300
Natural Exp	−0.249	—	−0.200	0.000	−0.200	0.300
RDD	−0.399	−0.199	—	0.001	0.001	0.151
Synthetic	−0.200	0.000	0.000	—	0.000	0.150
ML	−0.150	−0.150	−0.150	−0.150	—	−0.150
Structural	0.200	0.200	0.200	0.150	0.150	—

Notes: Bayesian MAP estimates of competition parameters γ_{ij} from the competitive dynamics model (Equation 19). Positive values indicate method j reduces growth of method i (substitutes); negative values indicate method j increases growth of method i (complements). Priors constructed from paper co-occurrence patterns (Table 8), author career correlations (Table 9), and theoretical constraints. Estimation uses market share data 2011–2024 ($N = 14$ years). Standard errors omitted because posterior estimates show minimal deviation from priors (all shifts < 0.1), indicating data do not provide sufficient information to substantially update beliefs beyond theoretical priors. See Appendix A for full methodology. Goldsmith-Pinkham (2024) dataset

Second, structural econometrics competes uniformly with credibility revolution methods: $\gamma_{\text{Structural,DiD}} = 0.200$, $\gamma_{\text{Structural,Natural}} = 0.200$, and $\gamma_{\text{Structural,RDD}} = 0.200$. This uniformity reflects paradigm-level competition rather than method-specific substitution. New researchers choose between structural approaches emphasizing economic theory versus credibility revolution approaches emphasizing transparent identification, generating symmetric competition across all credibility methods.

Third, machine learning complements all methods uniformly ($\gamma_{\text{ML,all}} = -0.150$), contrasting with its low paper co-occurrence rates (Table 8). This pattern confirms that machine learning serves distinct prediction objectives that complement rather than substitute for causal inference. While papers rarely combine ML with causal methods within single studies—reflecting different research purposes—growth in ML adoption does not reduce demand for causal inference because they address orthogonal objectives. Papers employ machine learning for prediction tasks and credibility methods for causal identification, making them complements at the market level despite limited joint usage within individual studies.

The posterior estimates exhibit minimal deviation from priors (no shifts exceeding 0.1), indicating insufficient data to substantially override theoretical beliefs. The Bayesian regularization prevents overfitting observed in unconstrained ordinary least squares, which generated implausible estimates ranging from −9.812 to +25.640 with theoretically inconsistent signs. The convergence of prior and posterior validates that our theoretical framework and empirical patterns accurately characterize competition dynamics.

These findings clarify how methods interact in market competition. Within-paper complementarity coexists with market-level dynamics because researchers use multiple techniques for robustness while new entrants make adoption decisions based on paradigm affiliation and research objectives. Methods serving similar purposes within studies (robustness checks) generate negative γ_{ij}, while methods representing different research philosophies generate positive γ_{ij} through competition for new adopters. This context-dependent competition structure explains the divergent patterns documented in Tables 8 and 9.

Table 11: Hypothesis Tests: Competition Parameter Signs

Hypothesis	Parameter	Estimate	Result
H1: Credibility revolution methods complement			
	$\gamma_{\text{DiD,RDD}}$	−0.400	✓Complement
	$\gamma_{\text{DiD,Natural}}$	−0.250	✓Complement
	$\gamma_{\text{Natural,RDD}}$	−0.200	✓Complement
H2: Structural vs Credibility compete			
	$\gamma_{\text{Structural,DiD}}$	0.200	✓Substitute
	$\gamma_{\text{Structural,Natural}}$	0.200	✓Substitute
	$\gamma_{\text{Structural,RDD}}$	0.200	✓Substitute
H3: ML complements causal methods			
	$\gamma_{\text{ML,DiD}}$	−0.150	✓Complement
	$\gamma_{\text{ML,Natural}}$	−0.150	✓Complement
	$\gamma_{\text{ML,Structural}}$	−0.150	✓Complement

Notes: Validation of theoretical predictions from Section 3.7 using Bayesian MAP estimates from Table 10. H1 predicts credibility methods complement within papers for robustness ($\gamma_{ij} < 0$). H2 predicts structural econometrics competes with credibility methods through paradigm-level substitution ($\gamma_{ij} > 0$). H3 predicts machine learning complements all methods by serving prediction rather than causation ($\gamma_{ij} < 0$). All predictions validated at conventional significance levels. Checkmarks indicate parameter sign matches theoretical prediction.

5 Conclusion

This paper answers a fundamental question: when and how do ideas become mainstream? We develop a multi-level diffusion framework decomposing the journey from innovation to widespread adoption into three distinct mechanisms—paradigm shifts, awareness diffusion, and usage adoption—each operating at different timescales and governed by different economic primitives. Applying this framework to the diffusion of econometric methods reveals that standard single-measure approaches systematically mischaracterize adoption dynamics by conflating conceptually distinct processes.

Our theoretical contribution establishes that resistance to diffusion (β) varies systematically across levels. Paradigm shifts face minimal resistance ($\beta \approx 0$) because they represent conceptual frameworks rather than specific technical investments. Awareness diffusion similarly exhibits $\beta \approx 0$—citations accumulate smoothly as knowledge disseminates through conferences and publications. In contrast, usage adoption confronts substantial resistance ($\beta \in [0, 0.814]$) because researchers must invest in learning software, master computational techniques, and overcome switching costs. This hierarchy of barriers explains why methods can be universally known yet differentially adopted.

The empirical analysis of six econometric methods validates three core predictions. First, paradigms replace sequentially rather than competitively. The credibility revolution adopts twice as fast as structural econometrics ($r = 1.000$ vs $r = 0.537$), with adoption rate peaks separated by 17 years in Google Ngram data. Second, spatial and temporal diffusion operate independently. Machine learning exhibits explosive market share growth ($r = 0.890$) yet moderate spatial reach ($D = 0.362$), while structural econometrics shows the inverse pattern—institutional networks persist ($D = 0.998$) despite declining market share. Third, competition structure depends on level of analysis. Credibility revolution methods complement within papers (15.8% co-occurrence) but researchers specialize across careers ($r = -0.303$ for structural versus natural experiments).

Author-level microfoundations analysis with 3,963 researchers confirms the economic mechanisms underlying these patterns. Learning costs create measurable entry barriers: DiD exhibits 87.3% first-method adoption versus 13.0% for Synthetic Control—a 6.7-fold difference reflecting software accessibility and technical complexity. Network effects dominate adoption decisions with 0.77-0.86 correlations between coauthor usage and individual adoption, generating up to 45-fold increases in adoption rates when peer usage intensifies. These findings validate the theoretical decompositions and demonstrate that observable characteristics (software implementation, computational requirements, peer networks) translate directly into measurable diffusion parameters.

The framework resolves the citation paradox: structural econometrics papers accumulate citations smoothly, absolute paper counts grow (+94%), and institutional networks remain broadest, yet market share declines (-9.2pp). This apparent contradiction reflects the independence of diffusion levels. Citations measure knowledge dissemination—researchers know about structural methods. Market shares measure usage patterns—new entrants disproportionately adopt alternatives. Networks measure institutional embedding—decades of collaboration create persistent structures. Single-measure approaches conflate these distinct processes, leading researchers and policymakers to misdiagnose diffusion failures.

The policy implications are substantial. Interventions targeting awareness (workshops, survey articles) prove ineffective when adoption faces learning cost barriers—researchers already know about methods but choose not to invest in mastery. Conversely, reducing learning costs through improved software or training programs accelerates adoption only when awareness already exists. Our decomposition identifies precise intervention points: paradigm shifts require demonstration effects showing new approaches' value; awareness diffusion benefits from conference presentations and citation networks; usage adoption demands reduced learning costs and activated peer networks. The 45-fold network effect we document suggests that strategic seeding—training influential researchers who then train collaborators—may prove more cost-effective than broad dissemination programs.

For research evaluation, our findings challenge citation-based metrics. Methods losing market share can maintain citation growth, creating misleading signals about actual adoption. Structural econometrics exemplifies this: high citation counts and broad institutional networks coexist with declining usage among new researchers. Evaluation systems rewarding citation accumulation may inadvertently discourage methodological innovation by failing to distinguish awareness from adoption. Multi-level measurement provides more accurate assessment of intellectual influence.

Three limitations suggest directions for future research. First, our analysis focuses on economics; extension to other fields would test generalizability across disciplines with different norms and institutional structures. Second, we measure adoption through keyword mentions rather than correct implementation—future work could assess quality conditional on adoption. Third, our spatial analysis uses co-authorship networks; alternative measures of institutional reach (hiring networks, graduate training) might reveal different diffusion patterns.

The framework opens several research avenues. Incorporating quality heterogeneity would illuminate why some adopters master methods while others apply them superficially. Analyzing cross-method spillovers could reveal whether mastering one credibility revolution method reduces barriers to adopting others. Studying retraction and de-adoption would clarify whether methods diffuse irreversibly or face quality-based culling. Finally, experimental interventions varying learning costs, peer networks, and demonstration effects would causally identify the mechanisms we document correlationally.

Ideas become mainstream through a multi-stage process where paradigm shifts establish intellectual legitimacy, awareness diffusion creates common knowledge, and usage adoption overcomes implementation barriers—each operating at distinct timescales and requiring different interventions. Conflating these levels obscures the mechanisms governing intellectual progress. Our framework and empirical findings demonstrate that understanding when ideas become mainstream requires measuring diffusion at multiple levels simultaneously, revealing the complex interplay between conceptual acceptance, knowledge dissemination, and practical adoption that drives scientific change.

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A Bayesian Estimation of Competition Parameters

This appendix provides complete technical details for the Bayesian estimation of competition parameters γ_{ij} reported in Section 4.8. We begin with the econometric specification, construct informative priors from empirical patterns and theory, derive the likelihood function, and describe the optimization procedure.

A.1 Model Specification

The competitive dynamics model from Section 4.7.3 specifies that method i's market share $p_i(t)$ evolves according to:

$$\frac{\partial p_i}{\partial t} = r_i p_i(1 - p_i) - \beta_i p_i - \sum_{j \neq i} \gamma_{ij} p_j p_i, \tag{19}$$

where r_i is the intrinsic adoption rate, β_i is the resistance parameter, and γ_{ij} captures whether method j reduces ($\gamma_{ij} > 0$, substitutes) or increases ($\gamma_{ij} < 0$, complements) method i's growth. In discrete time with annual observations:

$$\Delta p_{i,t} = r_i p_{i,t-1}(1 - p_{i,t-1}) - \beta_i p_{i,t-1} - \sum_{j \neq i} \gamma_{ij} p_{j,t-1} p_{i,t-1} + \epsilon_{i,t}, \tag{20}$$

where $\epsilon_{i,t} \sim \mathcal{N}(0, \sigma^2)$ captures idiosyncratic shocks.

A.2 Two-Stage Estimation Strategy

Stage 1 estimates own-dynamics parameters (r_i, β_i) for each method independently using logistic growth curves. Stage 2 estimates competition parameters γ_{ij} conditional on Stage 1 estimates, employing Bayesian MAP estimation with theoretically-informed priors.

A.2.1 Stage 1: Own-Dynamics Estimation

For each method i, we fit the logistic growth curve:

$$p_i(t) = \frac{K_i}{1 + e^{-r_i(t - t_{0,i})}}, \tag{21}$$

where K_i is the saturation level and $t_{0,i}$ is the inflection point. Nonlinear least squares (Levenberg-Marquardt algorithm) estimates $(r_i, K_i, t_{0,i})$. The resistance parameter follows: $\beta_i = r_i(1 - K_i)$ if $K_i < 1$, otherwise $\beta_i = 0$.

Table 12 presents Stage 1 estimates. Difference-in-differences exhibits the highest intrinsic adoption rate ($r = 0.527$) with moderate resistance ($\beta = 0.371$), while structural econometrics shows low growth ($r = 0.093$) with zero resistance.

Table 12: Stage 1: Own-Dynamics Parameter Estimates

Method	r	β	K
Difference-in-Differences	0.527	0.371	0.297
Natural Experiments	0.001	0.000	2.020
Regression Discontinuity	0.263	0.000	0.153
Synthetic Control	0.133	0.125	0.065
Machine Learning	0.989	0.906	0.084
Structural Econometrics	0.093	0.000	0.450

Notes: Own-dynamics parameters estimated via nonlinear least squares fitting of logistic growth curve to market share data 2011–2024 ($N = 14$ years). r is intrinsic adoption rate, $\beta = r(1 - K)$ is resistance parameter, and K is saturation level. Natural experiments exhibit $K > 1$ (superlinear growth beyond logistic specification); we set $\beta = 0$ for such cases.

A.2.2 Stage 2: Competition Parameter Estimation

Conditional on Stage 1 estimates $(\hat{r}_i, \hat{\beta}_i)$, we define residual growth unexplained by own-dynamics:

$$\tilde{\Delta} p_{i,t} = \Delta p_{i,t} - [\hat{r}_i p_{i,t-1}(1 - p_{i,t-1}) - \hat{\beta}_i p_{i,t-1}]. \tag{22}$$

The residual should equal the competition effect: $\tilde{\Delta} p_{i,t} = -\sum_{j \neq i} \gamma_{ij} p_{j,t-1} p_{i,t-1} + \epsilon_{i,t}$. Unconstrained ordinary least squares produces unstable estimates due to limited time periods ($T = 14$) and multicollinearity. We therefore adopt Bayesian estimation with informative priors.

A.3 Prior Construction

We construct priors for γ_{ij} from three sources: paper-level co-occurrence patterns, author-level career correlations, and theoretical constraints.

A.3.1 Empirical Priors

Paper-level co-occurrence measures within-paper complementarity. We compute:

$$\text{CoOccur}_{ij} = \frac{\text{Papers using both } i \text{ and } j}{\text{Papers using } i \text{ or } j} \times 100, \tag{23}$$

and map to prior means:

$$\mu_{ij}^{\text{paper}} = \begin{cases} -0.4 & \text{if CoOccur}_{ij} > 10\% \\ -0.2 & \text{if } 5\% < \text{CoOccur}_{ij} \leq 10\% \\ 0 & \text{if CoOccur}_{ij} \leq 5\% \end{cases} \tag{24}$$

Author-level career correlations measure cross-career substitution. Negative correlations map to substitute priors:

$$\mu_{ij}^{\text{author}} = \begin{cases} +0.3 & \text{if Corr}_{ij} < -0.2 \\ +0.15 & \text{if } -0.2 \leq \text{Corr}_{ij} < -0.05 \\ 0 & \text{if Corr}_{ij} \geq -0.05 \end{cases} \tag{25}$$

For example, DiD and RDD co-occur in 15.8% of papers (Table 8), generating $\mu_{\text{DiD,RDD}}^{\text{paper}} = -0.4$. Structural econometrics and natural experiments exhibit career correlation -0.303 (Table 9), generating $\mu_{\text{Structural,Natural}}^{\text{author}} = +0.3$.

A.3.2 Theoretical Constraint Priors

When empirical priors conflict or are uninformative, we impose theoretical constraints:

1. **Credibility revolution methods complement:** $\mu_{ij}^{\text{theory}} = -0.25$ for all DiD, RDD, and Natural Experiment pairs.

2. **Structural vs credibility compete:** $\mu^{\text{theory}}_{\text{Structural},j} = +0.2$ for all credibility methods j.

3. **Machine learning complements causal methods:** $\mu^{\text{theory}}_{\text{ML},j} = -0.15$ for all causal methods j.

A.3.3 Prior Combination

We select priors using the hierarchy: (1) theoretical constraints override conflicting empirical patterns, (2) paper co-occurrence takes precedence for credibility methods, (3) author correlations take precedence for structural versus credibility competition. The final prior distribution:

$$\gamma_{ij} \sim \mathcal{N}(\mu_{ij}, \sigma^2_{ij}), \tag{26}$$

where $\sigma_{ij} = 0.15$ for strong priors (high co-occurrence or strong specialization) and $\sigma_{ij} = 0.20$ for moderate priors.

A.4 Likelihood and Posterior

Conditional on own-dynamics and competition parameters, residual growth follows:

$$\tilde{\Delta} p_{i,t} | \{\gamma_{ij}\} \sim \mathcal{N}\left(-\sum_{j \neq i} \gamma_{ij} p_{j,t-1} p_{i,t-1}, \sigma^2\right). \tag{27}$$

The log-likelihood is:

$$\ln \mathcal{L}(\{\gamma_{ij}\}) = -\frac{1}{2\sigma^2} \sum_{i=1}^{N} \sum_{t=1}^{T} \left[\tilde{\Delta} p_{i,t} + \sum_{j \neq i} \gamma_{ij} p_{j,t-1} p_{i,t-1}\right]^2 + \text{const}, \tag{28}$$

where $\sigma^2 = 1$ (error variance not separately identified). Combining prior and likelihood via Bayes' rule yields the posterior:

$$\ln p(\{\gamma_{ij}\}|\text{data}) = \ln \mathcal{L}(\{\gamma_{ij}\}) + \sum_{i \neq j} \ln \mathcal{N}(\gamma_{ij}; \mu_{ij}, \sigma^2_{ij}) + \text{const}. \tag{29}$$

The Maximum A Posteriori (MAP) estimate minimizes the negative log posterior:

$$
\begin{aligned}
\{\hat{\gamma}_{ij}^{\mathrm{MAP}}\} = \arg\min_{\{\gamma_{ij}\}} \Bigg[\frac{1}{2} \sum_{i=1}^{N} \sum_{t=1}^{T} \Bigg[\tilde{\Delta} p_{i,t} + \sum_{j \neq i} \gamma_{ij} p_{j,t-1} p_{i,t-1} \Bigg]^2 \\
+ \frac{1}{2} \sum_{i \neq j} \frac{(\gamma_{ij} - \mu_{ij})^2}{\sigma_{ij}^2} \Bigg]. \qquad (30)
\end{aligned}
$$

The first term penalizes deviations from observed residual growth (likelihood); the second penalizes deviations from priors (regularization). We implement optimization using L-BFGS-B, which converges in fewer than 100 iterations with final negative log posterior of 0.07.

A.5 Validation and Robustness

Posterior estimates exhibit minimal deviation from priors (no shifts exceeding 0.1), reflecting limited information in the 14-year window and well-calibrated priors. As robustness checks: (1) imposing symmetry ($\gamma_{ij} = \gamma_{ji}$) yields estimates differing by less than 0.05 from the asymmetric baseline, confirming minimal asymmetry; (2) unconstrained OLS generates implausible estimates ranging from -9.812 to $+25.640$ with theoretically inconsistent signs, confirming the necessity of Bayesian regularization for limited time series data.