Competitive Dynamics and Emerging Technology: Industry, Regulation, and Discourse on Autonomous Vehicles

by

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Table of Contents

Acknowledgements ii

List of Tables vi

List of Figures viii

Abstract ix

Chapter 1 Introduction 1

1.1 Background 1

1.2 Competition as the Key Social Mechanism 3

1.3 Competition in Three Social Domains 6

1.4 Empirical Case: Autonomous Vehicles 9

1.5 Dissertation Overview 11

Chapter 2 Regulating Emerging Technologies: State Competition and Diffusion of Autonomous Vehicle Laws 14

2.1 Introduction 14

2.2 State Competition and Technology Regulations in Knowledge Economy 18

2.2.1 States as Strategic Regulatory Actors in the Knowledge Economy 18

2.2.2 Rethinking Interstate Competition: A Network Approach using Labor Mobility 20

2.3 Theories and Hypotheses 22

2.3.1 State Competition and Policy Adoption 22

2.3.2 State Competition and Policy Convergence and Divergence 23

2.3.3 Conditional Effects of Regulatory Capacity on Policy Convergence/Divergence 27

2.4 Empirical Setting 30

2.5 Methodology 33

2.5.1 Data 33

2.5.2 Analytical Strategies 34

2.5.3 Variables 35

2.6 Results 46

2.6.1 Policy Adoption Model 49

2.6.2 Policy Convergence and Divergence Model 52

2.7 Discussion 56

Chapter 3 Contextualizing the Framing Effects of Policy Adoption: Interstate Competition and Autonomous Vehicle Discourse in the U.S. 63

3.1 Introduction 63

3.2 Theoretical Framework 67

3.2.1 Policy Adoption as a Discursive Signal 67

3.2.2 The Contingent Framing Effects of Policy Adoption: The Role of Inter-State Competition 70

3.3 Research Setting 75

3.4 Methodology 77

3.4.1 Data and Sample 77

3.4.2 Measures 79

3.4.3 Analytical Approach 83

3.5 Results 85

3.5.1 Descriptives 85

3.5.2 Statistical Results 87

3.6 Discussion 96

Chapter 4 Clash of Industries: How Evolving Inter-Industry Competition Structures Alliance Behavior in the Autonomous Vehicle Sector 103

4.1 Introduction 103
4.2 Theoretical Framework 107
4.2.1 Strategic Alliance Theories and Business Ecosystem Theories 107
4.2.2 Inter-Industry Competition as a Structuring Logic 111
4.3 Inter-industry Competition in AV Field: Displacement Logic to Dependency Logic 113
4.3.1 Early Phase (2015-2019): Displacement Logic 115
4.3.2 Later Phase (2020-2024): Dependency Logic 118
4.3.3 Hypotheses on Alliance Behavior 122
4.4. Methodology 126
4.4.1 Data and Sample 126
4.4.2 Measures 129
4.4.3 Analytical Strategy 140
4.5. Results 141
4.5.1 Descriptive Patterns of Alliance Formation 141
4.5.2 Statistical Results 147
4.6. Discussion 159
Chapter 5 Conclusion 165
5.1 Summary 165
5.2. Theoretical Contributions 167
5.3 Methodological Contributions 168
5.4 Limitations and Directions for Future Work 170
Appendix 173
Bibliography 177

List of Tables

Table 2.1 Introduced and Enacted Bills by Topics 36

Table 2.2 Descriptive Statistics: Correlation Matrix for Enactment Model 47

Table 2.3 Descriptive Statistics: Correlation Matrix for Dyadic Model 48

Table 2.4 Logistic Regression on Enactment of Autonomous Vehicle Bills 50

Table 2.5 Logit Analysis of the Probability that State A moves toward State B on Bill Topic ... 53

Table 3.1 Average Treatment Effects of AV Policy Adoption on Frame Proportions, by Competition Context (Staggered Difference-in-Differences Estimates) 88

Table 3.2 Event Study Estimates of the Dynamic Effects of Policy Adoption on Frame Proportions, by Competition Context (Staggered Difference-in-Differences Estimates) 91

Table 4.1 Comparing Inter-industry Competition Logics 121

Table 4.2 Alliance Type Categorization 133

Table 4.3 Full Stack vs Infrastructure Patent CPC Codes 136

Table 4.4 Variable Description 139

Table 4.5 Descriptive Statistics 142

Table 4.6 Correlation Matrix between Continuous Variables 143

Table 4.7 Alliance and Partner Type Percentage (Displacement to Dependence) 146

Table 4.8 Binary logistic regressions predicting partner type (2015-2024) 148

Table 4.9 Binary logistic regressions predicting alliance types (2015-2024) 154

Table 4.10 Binary Logistic Regression predicting Redundant Alliances (2015-2024) 157

Appendix Table A.1 Examples of classification of AV related Paragraphs using SBERT similarity scores 173

Appendix Table A.2 Summary of Local Newspaper Corpus and Data Filtered by State 174

Appendix Table A.3 Illustrative Examples of Frame Classifications using SBERT similarity score 176

List of Figures

Figure 2.1 The Enactment of Autonomous Vehicles Regulations in the U.S. (2011-2021)..... 32

Figure 2.2 Diagram of Measuring Topic Convergence in Dyadic Level 37

Figure 2.3 Labor Mobility and State Competition Measures 40

Figure 2.4 Direct Competition Effect Conditional on Academic Expertise 55

Figure 3.1 Distribution of First-Year AV Policy Enactments across U.S. States (2012–2022) ... 85

Figure 3.2 Annual Trends in Autonomous Vehicle Frame Proportions across U.S. States (2012–2022) 86

Figure 3.3 Dynamic treatment effects (event study estimates) 92

Figure 4.1 Annual trends in partner types (2015–2024) 144

Figure 4.2 Annual trends in alliance types (2015–2024) 145

Figure 4.3 Marginal predicted probabilities of partner type by net logic and R&D spending ... 150

Abstract

Technological development is transforming not only markets and industries, but the institutional foundations of society itself. As new technologies disrupt established structures and create uncertain futures, understanding the social mechanisms that shape their development becomes essential. This dissertation centers competition as a key structuring mechanism by which actors across industry, government, and civil society navigate technological disruption, define strategic responses, and shape institutional outcomes. Rather than treating competition as a background market condition, I theorize it as a relational, evolving mechanism that influences how firms form alliances, how states regulate, and how public discourse is constructed.

Empirically, the dissertation examines the case of autonomous vehicles (AVs), a high-profile and infrastructurally intensive application of AI technologies. I investigate how competitive dynamics unfold across three social domains: regulation, discourse, and industry. Chapter 2 analyzes the regulatory domain, exploring how interstate competition influences the diffusion of AV regulations across U.S. states. Using a novel network-based measure of economic rivalry based on Census Job Flow data, I find that competition accelerates policy adoption but conditions whether states converge or differentiate in regulatory design. Chapter 3 examines the discursive effects of policy adoption in the context of media framing. Using Sentence-BERT and a corpus of 13,000 news articles, I show that in high-competition states, AV policies amplify economic and technological frames while suppressing ethical concerns, suggesting that competition structures not only institutional action but also public meaning-

making. Chapter 4 analyzes how inter-industry competition between automakers and technology firms shapes alliance behavior over time. Drawing on a dataset of 517 firm alliances (2015–2024), I show that firms shift from capability-seeking to dependency-management strategies as inter-industry competitive logics evolve.

Theoretically, the dissertation integrates insights from economic sociology, network theory, strategic management, cultural sociology, and policy diffusion, emphasizing competition as a field-level mechanism that evolves over time and shapes diverse institutional responses. Methodologically, the project combines quantitative alliance data, network-based policy diffusion models, and computational text analysis to trace how competition operates across domains.

Chapter 1 Introduction

1.1 Background

Recent technological developments are driving profound changes in the organization of modern society. Innovations in artificial intelligence, robotics, blockchain, and biotechnology are not only transforming how people work, communicate, and navigate daily life, but are also reshaping the institutional frameworks, social relationships, and power hierarchies that structure contemporary life (Benner and Tushman 2003; Geels 2004; Tushman and Rosenkopf 1992). These technologies are becoming deeply integrated into daily routines, policy systems, and economic structures. As they spread across different sectors, they bring new ways of organizing society while disrupting existing systems. This creates an urgent need to study how these technologies develop and influence social change (Zuboff 2019).

Among these emerging technologies, artificial intelligence (AI) has become a central force of disruption and reorganization. The rapid development and widespread deployment of AI systems, including predictive algorithms, large language models, and autonomous vehicles, are transforming industries, reshaping public institutions, and altering everyday practices (Klinger et al. 2020; Ziewitz 2016). Scholars have characterized this transformation using a variety of frameworks, including the Fourth Industrial Revolution (Schwab 2016), the Second Machine Age (Brynjolfsson and McAfee 2014), the Digital Revolution (Ford 2016), and the Artificial Intelligence Society (Inglehart 2018). These perspectives highlight not only the scale of

technological change, but also the deep restructuring it brings to labor markets, systems of expertise, governance regimes, and cultural norms (Eubanks 2018; Susskind 2020).

While many studies and public discussions focus on the transformative effects of AI, highlighting what it will change or how it will reorganize society, they often treat technological change as a linear or deterministic process. In reality, AI's development and adoption represent an ongoing process of co-production, in which technological systems and social institutions evolve together (Inglehart 2018). There is no predetermined outcome or singular future that AI will produce. Instead, its impacts are shaped by how it becomes embedded, interpreted, contested, and governed within specific social contexts (MacKenzie and Wajcman 1999). Understanding these dynamics requires close attention to the sociological mechanisms that structure this process.

In this dissertation, I argue that competition is a central structuring mechanism that governs how actors respond to technological change. When emerging technologies disrupt established arrangements, they create uncertainty, open new opportunity spaces, and unsettle existing hierarchies. In such moments, competition becomes especially salient. Actors must reposition themselves, make strategic claims, and contend with shifting boundaries and institutional ambiguity. Understanding how competition unfolds in these unsettled contexts is crucial for analyzing the broader social transformations driven by new technologies. Drawing on sociological theories of competition I plan to explore who, how, and why actors compete with each other when new technologies open up arenas of rivalry that did not previously exist.

To investigate this process, I focus on the case of autonomous vehicles, a paradigmatic example of artificial intelligence applied to everyday life. Through three empirical chapters, I analyze how competition operates across the domains of industry, regulation, and discourse.

Rather than treating competition as a background economic condition, I conceptualize it as a dynamic and relational process that evolves over time, shapes institutional responses, and influences which futures become possible (Abbott 2005; Fligstein 2001). By placing competition at the center of technological development, this dissertation offers a new perspective on how emerging technologies are not only engineered and regulated, but also socially constructed, contested, and institutionalized.

1.2 Competition as the Key Social Mechanism

Sociologists have long studied competition as a structuring force in social life. Max Weber famously defined competition as the "peaceful attempt to attain control over opportunities and advantages which are also desired by others" (Weber 1978 [1922]), emphasizing that competition emerges not from hostility, but from shared interest in a contested resource space. Georg Simmel (1964) conceptualized competition as a structural constellation: a patterned relationship between actors who orient themselves to the same resource, goal, or opportunity. Building on these classical foundations, contemporary sociologists have examined competition through a structural lens, emphasizing the positional and relational dynamics that shape competitive behavior. Network theorists have shown that an actor's position within a network profoundly shapes their exposure to competition, their strategic orientation, and ultimately their social actions and outcomes (Burt 2005; Podolny 2001). In this view, competition is not an abstract market force, but a socially structured and relational process.

Another major strand of sociological research on competition draws from field theory, particularly the work of Pierre Bourdieu (1990). Field theory conceptualizes competition as a struggle over position, legitimacy, and control of the rules that govern a given domain. In this framework, fields are structured social arenas in which actors compete not only for material

resources but also for symbolic capital (Bourdieu and Wacquant 1992). This perspective has deeply influenced institutional and organizational sociology. For instance, Fligstein and McAdam (2012) reframe fields as arenas of strategic action, where incumbents and challengers engage in ongoing relational contests shaped by shared understandings, rule structures, and asymmetries of power. In this tradition, competition is not reducible to market efficiency or survival imperatives; rather, it is a meaning-laden, socially constructed process through which actors pursue status, recognition, and the authority to define institutional trajectories.

Sociological approaches offer a distinct view of competition compared to mainstream economics. Whereas economic theories often view competition as an impersonal mechanism of market efficiency, driven by price signals, rational choice, and equilibrium-seeking behavior, sociologists emphasize that competition is a relational, socially embedded, and power-laden process (Fligstein 2001; Hartmann and Kjaer 2015; Simmel 1964). Actors do not simply respond to market conditions, but they interpret, contest, and strategically navigate their positions relative to others within structured fields (Burt 2005; DiMaggio and Powell 1983; Fligstein and McAdam 2012). Competition is not just about allocating resources but also about symbolic positioning, boundary-making, and struggles over legitimacy (Abbott 2005; Ingram and Yue 2008; Meyer and Hollerer 2010). As a result, understanding competition sociologically requires attention to how actors interpret their environments, engage in power struggles, and shape the dynamics and outcomes of rivalry (Hoffman et al. 2018; Inglehart 2018).

This dissertation draws on key insights from sociology to place competition at the center of analyses of technological development and social change. There are several reasons why competition deserves this central role. First, competition becomes especially salient in unsettled times, when technological breakthroughs disrupt existing resource configurations and field

dynamics. In more stable environments, the distribution of resources, institutional roles, and hierarchies tends to be well established, and competition often follows predictable, rule-bound patterns (DiMaggio and Powell 1983; Podolny 2001). But technological breakthroughs redefine what is valuable, who holds power, and how rivalry unfolds (Fligstein and McAdam 2012; Kaplan and Tripsas 2008). These disruptions generate uncertainty over status, jurisdiction, and institutional direction (MacKenzie and Wajcman 1999). As Arora-Jonsson et al. (2021) note, competition in such periods becomes more fluid and consequential, shaping which institutions endure and which visions of the future prevail (Bergek et al. 2013; Geels 2004; Jasanoff and Kim 2015). Understanding these dynamics is essential for analyzing how social order is renegotiated during technological change.

Second, competition related to technological development is not confined to markets but unfolds as a broader social process across domains and institutional levels. Technological disruption activates competitive dynamics among firms, states, professions, and global actors. At the geopolitical level, countries such as the U.S. and China compete for leadership in foundational technologies like artificial intelligence. Within national borders, states and cities vie to attract businesses, investment, and skilled labor by crafting favorable regulatory environments (Carruthers and Lamoreaux 2016). Within industries, firms not only innovate to stay ahead but also compete to define standards, control platforms, and shape future markets (Beneke 2019). These multiple arenas of competition illustrate how technological innovation reconfigures power and reshapes social fields well beyond the boundaries of the market.

Third, the effects of competition on technological development are not inherently positive or negative. Competition is a structuring force whose consequences depend on how it unfolds, which actors are involved, and the institutional context in which it operates. In some cases, it can

drive innovation, sharpen strategic decision-making, and improve institutional responsiveness. In others, it may lead to fragmentation, reinforce inequality, or marginalize ethical and social concerns (Hoffman et al. 2018; Silverman and Baum 2002). Precisely because of these ambivalent effects, competition should not be treated as a fixed attribute of markets or organizations, but as a dynamic and contingent social process. Since competition can produce divergent outcomes, analyzing how its dynamics unfold is crucial for grasping its broader social implications.

By placing competition at the center of analysis, this study contributes to a deeper sociological understanding of how emerging technologies are navigated, contested, and institutionalized. Examining competition across industry, regulation, and discourse sheds light on the strategic behaviors, symbolic struggles, and structural conditions that shape technological futures. In doing so, the dissertation reclaims competition as a vital analytical tool for sociology, one that is indispensable for explaining how societies respond to innovation under conditions of uncertainty and disruption.

1.3 Competition in Three Social Domains

This dissertation examines three social domains where competition plays a central role: industry, regulation, and discourse. These arenas represent distinct yet interrelated institutional fields where technological transformation is actively shaped and contested. They are also sites where competition is especially consequential, not only for how actors pursue advantage, but for how emerging technologies are institutionalized, governed, and publicly understood. By analyzing competition across these three domains, the dissertation captures the multidimensional nature of technological disruption and offers a more comprehensive account of how competitive

dynamics structure social change (Arora-Jonsson et al. 2021; Baum and Korn 1996; Hartmann 2015).

The first domain is industry, where competition is deeply intertwined with technological innovation, market positioning, and economic transformation. As emerging technologies create new opportunities, they trigger significant shifts in industrial structures. New firms emerge to occupy novel niches, while established firms strive to stay at the forefront of technological development. A defining feature of AI's industrial impact is its ability to blur the boundaries between previously distinct sectors, prompting firms to compete not only within industries but also across them (Bergek et al. 2013; Cozzolino and Rothaermel 2018). In this context, competition is no longer solely about price or market share, but it involves securing access to talent, controlling critical platforms, and establishing claims to technological leadership. Firms respond to this uncertainty by forming alliances, redefining boundaries, and strategically positioning themselves within newly emerging fields (Beckman et al. 2004; Hannah and Eisenhardt 2018). Understanding how competition structures these responses sheds light on broader patterns of organizational adaptation and strategic action in the face of innovation (Hillman et al. 2009).

The second domain is regulation, where interstate competition among states plays a central role in shaping how emerging technologies are governed. As systemic innovations like artificial intelligence unfold, state and local governments become active players in a competitive race to attract firms, talent, and investment. This rivalry often centers on crafting favorable regulatory environments that signal openness to innovation while balancing concerns around risk and accountability (Cao and Prakash 2012; Schneiberg and Bartley 2001). In this context, policy adoption is not only a matter of addressing technical or ethical concerns, but also a strategic

response to the actions of peer states. By analyzing interstate competition, we can better understand how rivalry between jurisdictions influences the pace, direction, and substance of policy innovation under technological uncertainty (Gilardi 2010; Shipan and Volden 2012).

The third domain is discourse, where public narratives surrounding emerging technologies are constructed, contested, and institutionalized. Discursive arenas do not simply mirror technological developments; they actively shape how technologies are interpreted, legitimized, and acted upon (Benford and Snow 2000; Jasanoff and Kim 2015). As new technologies gain prominence, various actors, including media outlets, policymakers, firms, and advocacy organizations, compete to frame their implications. These actors emphasize certain promises or risks, elevate particular values, and suppress alternative perspectives (Leonardi and Barley 2010). Such framing contests determine not only public understanding but also which visions of the future gain traction within institutions (Mohr et al. 2013). Understanding why some narratives become dominant requires attention to the competitive dynamics of discourse: who gets to speak, which frames resonate with institutional logics, and how symbolic signals amplify particular meanings within the broader cultural field (Meyer and Hollerer 2010; Wildt et al. 2022).

While other domains, such as education, science, or labor, are also shaped by competition under conditions of technological change, this dissertation focuses on industry, regulation, and discourse because they are especially central to the institutionalization of emerging technologies (Geels 2010). Since this dissertation analyzes distinct domains, it draws on distinct theoretical traditions from organizational sociology, field theory, policy diffusion, and network theory. Methodologically, this multidomain approach requires drawing on diverse data sources and measurement strategies tailored to each arena of analysis. Because competition takes different

forms across industry, regulation, and discourse, I develop domain-specific indicators that capture its varied expressions, a central contribution of this dissertation. Rather than treating competition as a fixed or uniform attribute, I operationalize it as a dynamic, relational process that unfolds differently across institutional contexts (Podolny et al. 1996). This approach not only deepens theoretical insight into competition but also provides methodological tools for analyzing how technological futures are shaped through structured forms of rivalry.

1.4 Empirical Case: Autonomous Vehicles

Autonomous vehicles (AVs), often referred to as self-driving or driverless cars, represent one of the most prominent and transformative applications of artificial intelligence (Stilgoe 2020). At the core of AI is the delegation of cognitive functions such as perception, decision-making, and adaptation to machines (Burns 2018). AVs incorporate these capabilities into the automobile, turning it from a passive mechanical device into an intelligent system capable of navigating complex environments without human intervention. Through the integration of machine learning, computer vision, and real-time sensor processing, the car becomes a responsive and autonomous actor which can perceive, interpret, and act within its surroundings (Anderson et al. 2016).

What makes this shift especially consequential is that AVs remove the need for a human driver. This change is not merely technical, but it challenges the foundational assumptions on which much of modern society has been built around car. Virtually all major systems surrounding mobility have been organized around the existence of the human driver. Industries are structured to sell, service, and insure vehicles operated by people. Transportation policy and legal frameworks are designed to regulate human behavior behind the wheel (Fagnant and Kockelman 2015). Urban infrastructures from road signage to parking systems presume human

judgment and error. Even expertise surrounding mobility, such as licensing, training, and liability, is based on the premise that a person is always in control (Anderson et al. 2016). Removing the driver destabilizes this entire constellation.

AVs are not merely a new transportation technology but a deeply disruptive force that reshapes multiple institutional arenas. Their development and adoption impact a wide range of social domains, including industry, regulation, professional expertise, public discourse, and everyday practices (Burns 2018; Kim et al. 2021; Stilgoe 2020). Because AVs cut across these different areas, they offer a unique opportunity to observe how a single technological innovation can catalyze widespread institutional transformation. As such, they serve as a compelling case for understanding how emerging technologies reorganize the structure and logic of contemporary society.

Central to this process is competition. AVs have become a key site of rivalry across diverse domains, concentrating struggles over technological innovation, regulatory authority, and symbolic legitimacy. In the private sector, firms race to secure patents, recruit top talent, and capture market share (MacDuffie 2018). Governments actively position themselves as innovation leaders by crafting favorable policy environments and attracting corporate investment (Carruthers and Lamoreaux 2016; Ford 2016). At the same time, regulatory agencies, professional groups, and public stakeholders vie to define standards for safety, liability, and ethics (Stilgoe 2020). These overlapping dynamics render AVs not just a technical project but a political and institutional battleground (Burns 2018).

The forms of competition surrounding AVs are multifaceted. Some are economic, involving struggles over capital, intellectual property, and platform dominance (Bergek et al. 2013). Others are symbolic, centered on legitimacy, standard-setting, and jurisdictional

leadership. Still others are discursive, as actors seek to frame AVs in ways that align with their interests, whether as symbols of progress, sources of risk, or instruments of social good (Jasanoff and Kim 2015). These contests unfold simultaneously and often intersect, making AVs a rich site for examining how competition operates across social fields. An exclusively economic view of competition is therefore insufficient; a sociological perspective is essential for understanding how competitive dynamics shape institutional structures (Bourdieu 1990; Fligstein and McAdam 2012; Hartmann 2015).

In this way, autonomous vehicles offer an ideal case for examining how competition governs behaviors and relationships in an era of rapid innovation. New forms of competition have emerged between and within social groups, and they are embedded across multiple levels of the social structure. Understanding the development of AVs, and the social processes through which they are framed, regulated, and adopted, also helps illuminate how other emerging technologies reshape the foundations of social order.

1.5 Dissertation Overview

This dissertation consists of three empirical chapters, each investigating how competition operates as a structuring mechanism in the development of autonomous vehicles (AVs) across different social domains. By examining the competitive dynamics in industry, state regulation, and public discourse, the project develops a multi-scalar, relational account of how actors navigate technological disruption through strategic positioning. Each chapter focuses on a distinct domain and draws from different literatures, but all share a common concern with how competition shapes social change.

Chapter 2 investigates competitive dynamics in the regulatory domain by analyzing how interstate competition shapes the diffusion of emerging technology policy, focusing on

autonomous vehicle (AV) regulation in the United States. Building on scholarship in policy diffusion and the knowledge economy, this chapter examines how U.S. states compete to attract firms and innovation by adopting forward-looking regulations. I test whether states facing greater competitive pressure are more likely to adopt AV-related policies and whether they tend to converge or diverge from their competitors over time. To capture competitive relationships, I develop a novel, network-based measure of economic competition using Census Job Flow data, which reflects patterns of inter-state labor mobility and economic interdependence. I also investigate how institutional factors, such as regulatory capacity and academic expertise, shape the direction of policy alignment. Through this analysis, the chapter aims to illuminate the mechanisms by which competition influences both the pace and pattern of technological policy diffusion across states.

Chapter 3 explores the discursive domain, analyzing how competitive context and policy decisions shape public narratives and framings about autonomous vehicles. While policy feedback theory suggests that policy adoption can reshape public framing and attitudes, existing research often overlooks the intergovernmental context in which these effects unfold. This chapter addresses that gap by theorizing policy adoption not just as a regulatory act but also as a symbolic signal, especially in states facing highly competitive pressure. I test whether AV policy adoption leads to shifts in local media framing and whether these discursive effects differ based on states' positions in the interstate competition landscape. Using a dataset of over 13,000 news articles published between 2012 and 2022, I apply Sentence-BERT to classify economic, technological, and ethical frames, and estimate policy effects using a staggered difference-in-differences (DiD) approach. This chapter contributes to our understanding of how policy actions

reverberate through the public sphere and shows that the discursive consequences of regulation are shaped by competitive dynamics across jurisdictions.

Chapter 4 examines competitive dynamics in the industrial domain by analyzing how firms respond to the convergence of the automotive and technology industries around autonomous vehicle (AV) development. As artificial intelligence shifts the core value of vehicles from mechanical engineering to software and data infrastructure, competition between industries has become a powerful structuring force. This chapter theorizes inter-industry competition as an evolving field logic that shapes firm behavior. I distinguish between two phases: an early "displacement logic," where tech firms posed existential threats to automakers, and a later "dependency logic," in which tech firms emerged as essential infrastructure providers. I hypothesize how these shifting logics influence alliance strategies, particularly among original equipment manufacturers (OEMs). Drawing on network theory, strategic alliance research, and business ecosystem literature, I analyze patterns in OEM alliance formation. This chapter contributes to theories of industry convergence and strategic collaboration by demonstrating how inter-industry competition structures both the partner and the forms of inter-firm alliances.

Taken together, these three chapters provide a sociological account of how competition structures technological development across institutional domains. Rather than treating competition as a background condition, I conceptualize it as a dynamic and evolving mechanism that shapes how actors respond to disruption, claim legitimacy, and attempt to structure the future. By tracing competition across industry, regulation, and discourse, the dissertation highlights how emerging technologies like AVs contested, framed, and institutionalized through structured forms of rivalry.

Chapter 2 Regulating Emerging Technologies: State Competition and Diffusion of Autonomous Vehicle Laws

2.1 Introduction

As technological advancement and economic growth become increasingly intertwined, state governments in the U.S. are actively employing regulatory policy as a strategic tool for economic development (Mandel 2009; Moses 2013). In today's knowledge-based economy, regional prosperity depends on cultivating a robust industrial base and attracting high-value firms and skilled labor (Genschel and Seelkopf 2015; Karvonen 2020). Crafting effective regulations in areas such as artificial intelligence, autonomous vehicles, and blockchain has become central to this effort. States are no longer passive responders to technological innovation, but they actively shape regulatory frameworks to gain competitive edge (Jessop 1998; Walker-Smith 2016). In this context, regulatory policymaking has become a critical domain in which states compete to attract investment, innovation, and talent. This shift raises critical set of questions: How does interstate competition shape the diffusion of technology regulations and their substantive content? Do states under competitive pressure converge on similar topics of regulations, or do they strategically diverge? And how should we measure competition in ways that reflect the realities of a knowledge-driven economy (Gilardi and Wasserfallen 2019)?

A long-standing tradition in policy diffusion research has identified competition as a central driver of policy adoption (Berry and Berry 1990; Dobbin et al. 2007; Gilardi 2010). The core premise is that policymakers actively monitor the actions of their peers and strategically adjust their own policies to gain or sustain economic advantages (Volden 2002). This insight has

produced a robust body of literature examining how competitive pressures shape state-level policymaking, particularly in domains related to economic development such as labor markets, taxation, environmental regulation, and corporate governance (Bailey and Rom 2004; Carruthers and Lamoreaux 2016; Elkins et al. 2006). Despite its foundational role, however, the competitive diffusion literature suffers from two key limitations.

First, the literature on competitive diffusion has primarily focused on examining "race to the bottom" or "race to the top" dynamics, both of which represent forms of policy convergence (Carruther and Lamoreaux 2016; Radaelli 2004; Volden 2002). In these accounts, states are depicted as collectively lowering or raising regulatory standards in pursuit of economic advantage. This convergence-focused lens often stems from studies examining policies with a single, easily quantifiable dimension such as tax rates or welfare spending (Berry and Berry 1990; Elkins et al. 2006). However, such a framework is poorly equipped to capture the complexity and multi-dimensionality of emerging technology regulations. These policies frequently encompass a wide array of topics including licensing, liability, and data governance, each of which offers distinct opportunities for strategic differentiation. When regulatory issues span multiple domains, policymakers may not only imitate competitors but also seek to differentiate themselves by emphasizing particular topics, creating a unique regulatory niche.

Second, the competitive diffusion literature has struggled with the conceptualization and measurement of competition that accurately captures the context of the case. Rather than finding the matched competition measure, many empirical studies have relied on geographic contiguity as a proxy for competition, assuming that states primarily compete with their immediate neighbors. This measure is widely criticized as a "catch-all indicator" that cannot effectively differentiate between true economic competition and other mechanisms like social learning or

simple emulation (Graham et al. 2013; Karch 2007; Maggetti and Gilardi 2015). More importantly, it reflects an outdated model of economic reality. In a knowledge economy where the most valuable assets such as skilled labor and investment capital are highly mobile, the true competitive landscape is not defined by shared borders but by interlinked labor markets and overlapping economic activity across states.

To address these limitations, this study moves beyond conventional "race to the bottom" models by empirically testing whether interstate competition leads to convergence or divergence as distinct strategic responses within a knowledge-based economy. Drawing on two contrasting theoretical traditions of competition, one emphasizing imitation and convergence (Beckert 2010; Berry and Berry 1990; Dobbin et al. 2007) and the other highlighting differentiation and strategic innovation (Ingram and Yue 2008), I formulate hypotheses that treat both policy convergence and divergence as plausible outcomes of competitive pressure. This approach challenges the dominant focus on convergence in the existing literature by recognizing that regulatory differentiation can also serve as a strategic response (Baybeck et al. 2011; Graham et al. 2013). I then extend the analysis to examine the conditions under which each outcome is more likely to occur. Recognizing that competition does not operate in a vacuum, I explore the moderating role of state regulatory capacity, arguing that internal expertise may shape whether a state imitates its competitors or pursues an independent regulatory path (Gilardi and Füglister 2008; Jansen et al. 2016).

To test these hypotheses, I introduce an innovative network-based measure of competition that is grounded in the realities of the knowledge economy. While international policy diffusion literatures have utilized network conceptualizations of competition, such as trade flows, capital flows, and foreign direct investment (FDI) flows (Hafner-Burton 2009; Maoz et al.

2006), their application to interstate competition within the U.S. context remains limited. This study overcomes that gap by constructing a national labor mobility network using the U.S. Census Bureau's Job-to-Job (J2J) Flows data (Görg and Strobl 2005; Hyatt et al. 2018; Magnani 2009). By tracking the movement of workers between states in specific industries, this measure captures the real-world dynamics of competition for human capital which is an essential driver of modern economic strategy. Drawing on network theory, I use these data to construct two measures of competition: direct competition and structural equivalence, following classic approaches to network-based rivalry (Burt and Talmud 1993; Ingram and Yue 2008).

I test these hypotheses using the case of autonomous vehicle (AV) regulation in U.S. states. This domain is especially well-suited for studying competitive diffusion because, in the absence of a federal framework, states have taken the lead in crafting AV policies, resulting in significant cross-state variation (Anderson et al. 2016). AVs are also economically significant, offering opportunities for states to attract firms, investment, and skilled workers through favorable regulation (Burns 2018). Importantly, AV regulation is not a single-dimensional policy but spans multiple components, including safety, liability, infrastructure, and data governance, allowing states to either imitate others or differentiate their approach to gain strategic advantage (Maurer et al. 2016). This makes AV regulation an ideal case to examine not only when states adopt policies, but also how competition shapes the substantive content of those policies.

Using data on all AV-related bills compiled by the National Conference of State Legislatures (NCSL) from 2011 to 2021, I employ a two-pronged analytical strategy. First, I use Event History Analysis (EHA) to assess whether my network-based measures of competition predict the likelihood that a state adopts an AV policy (Berry and Berry 1990). Second, I apply dyadic modeling to examine whether competition leads to convergence or divergence in policy

content, and under what conditions these outcomes are more likely to occur, particularly focusing on the moderating role of state regulatory capacity (Boehmke 2009; Gilardi and Füglister 2008).

2.2 State Competition and Technology Regulations in Knowledge Economy

To empirically assess how competition shapes the diffusion of technology policies, it is critical to situate competition within its broader socio-economic context and to construct measures that reflect this context with precision (Gilardi and Wasserfallen 2019; Graham et al. 2013). I begin by conceptualizing the relationship between emerging technology policy, interstate competition, and the evolving techno-economic landscape in which they are embedded (Moses 2007). I then define how I conceptualize state-level competition and detail how this concept is operationalized in the analysis that follows.

2.2.1 States as Strategic Regulatory Actors in the Knowledge Economy

How do states compete, and on what do they compete, in a knowledge-intensive economy[1] where technology is the core part of industry? In this new economic landscape, the interplay between industry, technology, and regulations significantly influences the economic development of states, forming the foundation of their competitive dynamics (Karvonen 2020; Mandel 2009; Moses 2007). I argue that states compete for businesses, investment, and talent by strategically shaping their regulatory frameworks for emerging technologies (Konisky 2007). Local regulatory bodies strategically craft their technological regulations to establish an

[1] A new period with the advent of artificial intelligence and other emerging technologies are described with a range of expressions such as Fourth Industrial Revolution (Schwab 2016), Digital Revolution (Brynjolfsson and McAfee 2014), and Artificial Intelligence Society (Inglehart 2018). Since there is no agreement on a single term, I will use "knowledge economy" temporarily in this proposal.

attractive legal environment for new investments or to retain existing ones, thereby gaining a competitive edge over other states (Jessop 1998; Wiener 2004).

Economic geographers have long emphasized the strategic role of policymakers in shaping regional economic growth. Rather than viewing local governments as passive responders to national trends, scholars argue that economic development increasingly becomes a core function of local governance (Wilson 2014). Harvey (1989) notably observed a shift from managerialism to entrepreneurialism in urban planning, as cities began to actively pursue investment and economic dynamism. Subsequent research has elaborated on this perspective by examining how regional actors engage in proactive efforts to attract capital, talent, and infrastructure (Karvonen 2020; Rickard 2020; Wilson 2014). Over time, local governments have evolved from primarily providing welfare services to actively promoting economic competitiveness (Geels 2010; Genschel and Seelkopf 2015; Jessop 2002). These efforts are increasingly shaped by the demands of a knowledge-based economy, globalization, and the rise of the Fourth Industrial Revolution (Inglehart 2018). Building upon the scholarly discourse on economic competition between states and the impacts of broader economic paradigms, I establish a theoretical framework for comprehending the relationship between state competition and technology regulations.

Why is technology regulation a key component of state competition in the knowledge-intensive economy? I suggest two ways that technology is related to state competition. First, technology is the core of the knowledge-intensive economy and is closely intertwined with industry (Cole and Bertenthal 2017). The technological landscape of a region shapes the industrial base of that region. Consequently, the types of technology endorsed by a region define its economic character (Genschel and Seelkopf 2015). In light of the rapid emergence of new

technologies like artificial intelligence, blockchain, and the Internet of Things, the ability to attract technology-related businesses and skilled workers to a given region becomes paramount for its survival and economic prosperity (O'Shaughnessy et al. 2023; Schiff et al. 2020). Technology acts as a magnetic force, luring in firms and a skilled workforce (Karvonen 2020).

Second, technological development coevolves with regulations. Technology and regulations are often portrayed as adversaries, with regulations seemingly acting as constraints that inhibit technological progress (Moses 2013). However, recent research suggests that regulations can, in fact, foster innovation (Walker-Smith 2016). This is particularly relevant in the case of emerging technologies, as technology requires a societal foundation, often provided by regulations, for its development (Mallinson et al. 2013; Schiff et al. 2020). The relationship between law and technology is not one of mere reaction but of co-construction (Faulkner et al. 2012; Jasanoff 2004). Therefore, for businesses and professionals involved in advancing new technologies, the choice of a particular region hinges not solely on the technical competencies present but also on the region's legal environment and regulatory framework (Mandel 2009; Moses 2007; Silbey 2009). It is the role of state governments to actively develop and innovate regulations concerning emerging technologies to vie with other states for economic advantages.

2.2.2 Rethinking Interstate Competition: A Network Approach using Labor Mobility

Understanding how states compete in the knowledge economy requires both identifying relevant domains of rivalry and developing measures that align with theoretical definitions of competition. A major limitation in existing research is the reliance on geographic contiguity as a proxy, which assumes neighboring states are natural competitors. This approach has become increasingly problematic, as it often fails to reflect economic competition and it functions as a catch-all indicator that blurs important distinctions between competition, learning, and emulation

(Gilardi 2016; Maggetti and Gilardi 2015). To address this, I introduce a network-based framework that leverages inter-state labor mobility to identify competitive relationships. By focusing on where talent flows and how states are economically interconnected, this approach offers greater conceptual clarity and empirical precision in capturing the dynamics of interstate competition in the contemporary knowledge economy.

In the knowledge economy, human capital is a critical resource, and attracting skilled workers is central to regional economic strategy (Hiscox 2001; Hyatt et al. 2018; Magnani 2009). State governments compete by designing regulatory environments that make them attractive destinations for mobile talent (Görg and Strobl 2005; Heggedal et al. 2017). Labor mobility thus serves as a meaningful indicator of economic competition. Following this logic, I use the U.S. Census Bureau's Job-to-Job Flows dataset to measure worker movements between states. This dataset captures fine-grained flows of workers across industries and geographic boundaries, enabling a robust mapping of competitive relationships in the labor market (Jansen et al. 2016).

Building on this foundation, I will employ a network-based framework for measuring competition. Social scientists have long used network approaches to analyze and measure competitive relationships across a range of domains (Burt 1993; Guler et al. 2002; Ingram and Yue 2008). For example, in international policy diffusion studies, scholars commonly use trade flows, capital movement, and foreign direct investments (FDI) to map global competition (Greenhill et al. 2009; Hafner-Burton et al. 2009; Ward et al. 2011). However, this network approach has rarely been applied to interstate dynamics within the U.S., in part due to data limitations (Desmarais et al. 2015). The availability of high-resolution labor mobility data now makes such an analysis feasible.

Drawing on network theory, I will operationalize interstate competition using labor mobility data, focusing on two competition measures: direct competition and indirect competition, the latter measured through structural equivalence. Direct competition captures the volume of labor outflows between states within related industries, signaling active rivalry over skilled workers (Guler et al. 2002). Indirect competition, by contrast, reflects structural equivalence, situations in which states compete for similar pools of labor from the same third-party states, even if they do not exchange workers directly (Burt 1987; Strang and Tuma 1993). A detailed explanation of how these measures are constructed is provided in the methodology section. I argue that these network-based indicators offer a more accurate and theoretically grounded way to capture the dynamics of competition in a mobile, knowledge-driven economy.

In the following section, I draw on theories of policy diffusion and competition to formulate hypotheses about how interstate competition shapes both policy adoption and the dynamics of convergence and divergence

2.3 Theories and Hypotheses

2.3.1 State Competition and Policy Adoption

Policy diffusion research has long emphasized that jurisdictions influence one another, and that the policy choices of one government are shaped by the decisions of others (Mooney 2020; Vasi and Strang 2009). Among the key mechanisms driving this process, competition has been identified as a critical force explaining why policymakers adopt certain policies (Dobbin et al. 2007). States strategically craft regulations to attract business investment and other economic assets, seeking to gain an edge over rival states (Volden 2002). In this view, regulation spreads through competitive diffusion when a state adopts a policy not only for its own benefit, but to preempt or respond to similar actions by competitors (Konisky 2007; Shipan and Volden 2008).

A growing body of research has documented how diverse economic incentives have shaped such diffusion dynamics (Carruthers and Lamoreaux 2016; Radaelli 2004).

Building on this foundation, I argue that in the domain of emerging technologies, competition among states increasingly revolves around the ability to attract firms, skilled workers, and technological capital through crafting regulation (Moses 2013; Stilgoe 2018). Therefore, I expect that a focal state will feel pressured when the number of competing states adopting technology regulations increases. The focal state will be likely to adopt technology regulation due to those competitive pressures. In particular, I argue that the network-based competition measure I develop will be a statistically significant predictor of policy adoption, even when accounting for conventional measures of competition such as geographic contiguity and Bureau of Economic Analysis (BEA) economic areas (Konisky 2007; Maggetti and Gilardi 2015). Thus, I hypothesize that:

Hypothesis 1: *Competitive pressure increases the likelihood of policy adoptions.*

2.3.2 State Competition and Policy Convergence and Divergence

Next, I will examine whether competition leads to policy convergence or divergence[2]. Will policies in different jurisdictions align or diverge in response to economic competition? Two strands of theories propose opposing outcomes regarding the effects of competition on convergence and divergence behaviors (Barnett et al. 2021; Baum and Haveman 1996; Deephouse 1999; Ergen and Kohl 2020). They predict that competitive pressure can lead to imitation and conformity in some instances, while in others, it may drive divergence and differentiation (Deephouse 1999). Both imitating and differentiating can be considered viable

[2] Research on policy diffusion has primarily focused on policy adoption (Gilardi and Wasserfallen 2019), however, an increasing amount of research emphasizes that analyzing the determinants of the content of bills is important for understanding policy diffusion.

strategies for actors when they encounter competitive pressure (Radaelli 2004). Therefore, I will formulate a set of hypotheses regarding the influence of competition on the convergence and divergence of technology regulations. Subsequently, I will investigate the conditions under which I can expect policies to either converge with or diverge from those of competitors.

Extensive research has explored why competition tends to drive similar behaviors that result in the convergence of social practices (Burt 1987; Lieberman and Asaba 2006). Institutionalists argue that in competitive markets, organizations may emulate the practices and structures of successful competitors or industry leaders to establish their legitimacy and gain acceptance within the industry (Guler et al. 2002). Strategy studies emphasize that imitating competitors can be a risk-minimization strategy since differentiating from competitors can be a risky approach (Lieberman and Asaba 2006). Network theorists have shown that the pressure to imitate competitors arises from the necessity to safeguard one's market position and social standing (Burt 1987; Guler 2002). Resource dependence theories anticipate that competing organizations, reliant on similar resources, will adopt similar strategies and behaviors to maintain access to vital resources (Cao and Prakash 2012; Lee and Strang 2006).

In a similar vein, policy literature has shown imitating behaviors among competitors. Several theories have investigated policy convergence, seeking to understand why different jurisdictions adopt similar policies over time and how competitive pressure contributes to regulatory uniformity (Henisz et al. 2005, Holzinger et al. 2008; Meyer et al. 1997; Polillo and Guillén 2005). The theories of world society, neo-institutionalism, and world politics have all identified competition as one of the factors that drive policy convergence, alongside other mechanisms like imposition, harmonization, and emulation (Drezner 2005; Knill 2005). The underlying concept is that competition can create isomorphic pressures, assuming that countries

are competing to offer favorable institutional conditions for mobile production factors (Elkins et al. 2006). Specifically, globalization theorists anticipate that countries adjust their policies and regulatory standards in response to competitive pressures arising from economic integration (Cao 2020; Elkins et al. 2006; Simmons and Elkins 2004). In line with this logic, the "race to the bottom" and "race to the top" arguments have been widely studied as examples of policy convergence (Radaelli 2004).

These policy convergence studies offer valuable theoretical insights to our case of technology policy diffusion (Guillén 2001). As emerging technologies disrupt existing social structures of competition, state governments are inclined to imitate the regulatory approaches of competing states as uncertainty is high (Holzinger and Knill 2005). This imitation strategy aims to minimize risks and ensure they remain competitive in evolving regulatory landscapes. Specifically, states are likely to adopt similar policies as states with which they are competing in the same labor market to avoid falling behind their rivals (Elkins et al. 2004; Guler et al. 2002; Polillo and Guillén 2005). Hence, I hypothesize that,

Hypothesis 2-1: *Competitive pressure drives convergence of policy topics between competing states.*

Another well-established literature in the social sciences posits that competition fosters differentiation. Strategically diverging from one's competitors is seen as a means to secure a more favorable economic or social position (Deephouse 2009). Economic strategy theories contend that competition is about being different or standing out (Lieberman and Asaba 2006). Niche theory, rooted in ecology, offers valuable insights into these studies (McPherson 1983). Scholars in population ecology argue that firms or organizations can survive by developing market niches (Hannan and Freeman 1984). Intense competition can propel organizations to

develop unique products, services, or branding strategies, enabling them to establish their own distinct niche (Baum and Haveman 1997; Carroll and Hannan 2000). In network theory, White (1981) demonstrates that producers mutually observe one another and strive to specialize, thereby occupying a niche not already claimed by competitors, consequently fostering product diversity in the market.

The literature on policy divergence shares similar principles when it comes to explaining how competition stimulates the differentiation of policies among states. In political economy, the Varieties of Capitalism School (Hall and Soskice 2001; Thelen 1999) and Business Systems theories (Whitley 1999) have both regarded international competition as a catalyst for cross-national divergence rather than convergence. This perspective arises from the idea that competition enhances institutional comparative advantages. According to these scholars, state governments strategically choose policy divergence to gain a competitive edge by using regulations to attract new industries, thus setting themselves apart from competing states (Knill 2005). States benefit from regulatory competition not by becoming more similar but by differentiating to have institutional advantages (Hall and Soskice 2001). This perspective aligns with niche theories in social sciences that I discussed above. Consequently, states or nations come to occupy distinct and relatively stable "regulatory niches" (Radaelli 2004).

In this study, I also argue that differentiation, achieved through niche development, serves as an incentive for states to diverge in their approach to technology regulations compared to their competitors (Hansson 2020; Roth 2020). Since technology regulations can contain multiple topics to be developed (Parinandi 2020), state governments can choose to create regulatory niches to attract mobile production factors. Therefore, I expect that diversifying from

their competitors can be a more effective strategy than simply copying the policies of competing states (Mintrom 1997). Thus, I hypothesize that,

Hypothesis 2-2: *Competitive pressure drives divergence of policy topics between competing states.*

2.3.3 Conditional Effects of Regulatory Capacity on Policy Convergence/Divergence

The effects of competition on policy convergence and divergence might be contingent on specific conditions. Policy diffusion scholars have stressed that the diffusion mechanisms do not operate identically for all policy domains and policymakers (Gilardi 2016; Konisky 2009; Wimmer 2021). Therefore, I aim to specify the conditions under which state policymakers are more likely to diverge from or converge with their competitors in response to competitive pressures (Mooney 2020).

In this study, I argue that the effects of competitive pressure on convergence and divergence are conditioned by regulatory capacity. Existing literature has underlined the critical role played by actor capacities, encompassing their capacity to learn, compete, or exert influence (Gilardi 2016; Mintrom 1997; Zhou 1993). Scholars have demonstrated that the diffusion process can be shaped by these regulatory capacities (Boehmke 2009; Hanson and Sigman 2021). Shipan and Volden (2013) have demonstrated that learning is influenced by the level of professionalization within state governments, while Zhou (1993) has shown that a greater economic capacity is associated with the likelihood of policy adoption.

There are different ways to conceptualize regulatory capacity, but I focus on state expertise as the key characteristic that moderates the convergence and divergence of policies (Berwick and Christia 2018). Expertise is particularly important in my case because technology regulation is a complex policy. Scholars have emphasized that policy characteristics are

important in the diffusion process, and the complexity of policy is an important factor (Nicholson-Crotty 2009). Technology regulations are evidently complex policies due to their demand for a high level of knowledge and expertise (Haas 1989; Makse 2021). Therefore, addressing this complexity requires a broader conception of regulatory capacity, one that includes expertise. The central argument is that states with higher levels of relevant expertise are better equipped to strategically pursue divergent policy paths in complex regulatory domains. In contrast, states lacking such expertise are more likely to adopt imitative strategies, aligning their policies with those of competitors (Bromley-Trujillo et al. 2021). In this study, I focus on two key dimensions of regulatory expertise: academic expertise and political expertise.

First, I view academic expertise as a pivotal component of regulatory capacity in technology policies (Mason 2016; Weible 2008). A body of literature has delved into the role of academic experts and epistemic communities in the policymaking process (Bromley-Trujillo et al. 2021; Graham, Shipan, and Volden 2013; Heikkila and Gerlak 2013). Epistemic communities, which coalesce around specific policy domains and share principled and causal beliefs, wield considerable influence over policy diffusion (Makse 2021; Parthasarathy 2010; Rose 1991). These expert groups conceptualize novel policy solutions and furnish policymakers with rationales for their adoption (Haas 1989; Soule and King 2008; Strang and Meyer 1993). Academic knowledge becomes especially critical when shaping policies related to science and technology, spanning areas such as embryonic stem cells, GMOs, vaccination, environmental change, and biotechnology (Karch 2012). These experts offer valuable insights into how to approach and frame these intricate issues.

Therefore, I contend that academic experts represent substantial capacities within each jurisdiction. I anticipate that academic expertise holds the potential for states to innovate or

diverge from their competitors by introducing new ideas or policies. However, if a state does not have enough academic expertise, it is less likely to be innovative in technology regulations and they are more likely to imitate competing states to stay competitive. Therefore, I hypothesize:

Hypothesis 3-1: *States with greater academic expertise are more likely to diverge their policy topics from their competitors.*

The second aspect of regulatory capacity is political expertise, often referred to as legislative professionalism. As defined by Squire (2017), legislatures that exhibit a higher degree of professionalism tend to possess enhanced evaluative capabilities. The level of political expertise within state legislatures can vary significantly by states. For example, certain states provide substantial remuneration to their lawmakers and offer robust staff support to assist them in fulfilling their roles. Conversely, some states provide limited compensation and minimal staff assistance. Additionally, there are disparities in the establishment of committee systems, with some states having well-developed systems while others do not (Basseches et al. 2022; Bowen and Greene 2014; Squire 2017). Furthermore, the frequency of legislative sessions varies, ranging from year-round meetings in some states to only a few weeks per year or biennial sessions in others (Shipan and Volden 2006).

These variations among state legislatures represent the difference in legislative professionalism. Legislatures that convene more frequently, provide higher salaries, and have more robust support structures, including staff and committees, are typically considered more professionally oriented compared to their counterparts (Bowen and Greene 2014; Shipan and Volden 2013). Members of well-resourced legislatures can dedicate more time and effort to policy analysis, including the examination of other states' experiences (Boehmke 2005; Jansa et al. 2019). As Squire points out, highly professionalized legislatures are often better equipped to

independently generate information (Squire 2017). Therefore, they can formulate policy ideas tailored to the specific needs of their states, often without relying on the experiences of other states. This enables states to differentiate from competing states. Thus, I hypothesize that,

Hypothesis 3-2: States with greater political expertise are more likely to diverge their policy topics from their competitors.

2.4 Empirical Setting

Autonomous vehicle (AV) regulation presents an analytically rich case for theorizing interstate competition in a knowledge-intensive economy and for examining how such competition shapes both the adoption and content of state-level regulations. Several features make this policy domain especially well-suited for studying competitive diffusion and the tension between policy convergence and divergence.

First, autonomous vehicle regulation offers a powerful lens for examining the intersection of technological innovation and regional economic development. AV technology is not only a high-profile technological frontier, but also a sector deeply entwined with the dynamics of local economic growth (Hildebrand 2019). Because AVs integrate software, hardware, infrastructure, and data systems, their development and deployment span a wide range of industries that many of which are concentrated regionally. As such, AV regulation is not just about transportation or safety, but it is a vehicle for states to align themselves with the future of industrial transformation (Maurer et al. 2016). This makes AV regulation a particularly compelling case for theorizing how states compete within a knowledge-intensive economy, where emerging technologies become central to industrial policy and regional competitiveness.

Second, AV regulation illustrates how states actively use regulatory policy to compete for economic advantage. In the absence of binding federal standards, states have considerable

freedom to shape their own AV policies. Many leverage this autonomy to attract investment, talent, and firms by promoting themselves as innovation-friendly jurisdictions. Regulation becomes a signaling device, used to demonstrate a state's readiness to host next-generation industries. In this way, regulation is not simply a reactive tool for managing technology, but it is an active instrument of economic positioning in an interjurisdictional competitive landscape (Hansson 2020; Stilgoe 2020).

Third, AV regulation is particularly well-suited for analyzing policy convergence and divergence in content. Unlike many regulatory domains that center on a single issue or threshold, AV regulation spans multiple dimensions, such as vehicle testing protocols, insurance requirements, cybersecurity, data privacy, operator licensing, and infrastructure standards. This multidimensionality enables states to selectively emphasize, combine, or omit specific regulatory elements, resulting in varied configurations of policy content. Such variation provides an ideal setting to move beyond binary diffusion models like the "race to the top" or "race to the bottom," allowing for a more granular examination of how states align with or differentiate from one another in the substance of their regulations. This perspective also enriches our understanding of interstate competition: states compete not only over whether to regulate, but over how to define their regulatory identity through topic selection.

Fourth, the absence of comprehensive federal regulation further underscores the value of AV policy as an empirical setting for examining variation in both policy adoption and content. Although the U.S. Department of Transportation and the National Highway Traffic Safety Administration (NHTSA) have issued voluntary guidelines, these lack binding authority and leave considerable discretion to individual states (Walker-Smith 2014). Consequently, AV regulation in the U.S. has evolved into a decentralized patchwork of state-level initiatives, with

each state responding uniquely to its political, economic, and institutional context (Roth 2020). States are tasked with determining how AVs are integrated into existing frameworks for traffic enforcement, insurance, licensing, registration, and liability (Walker-Smith 2016).

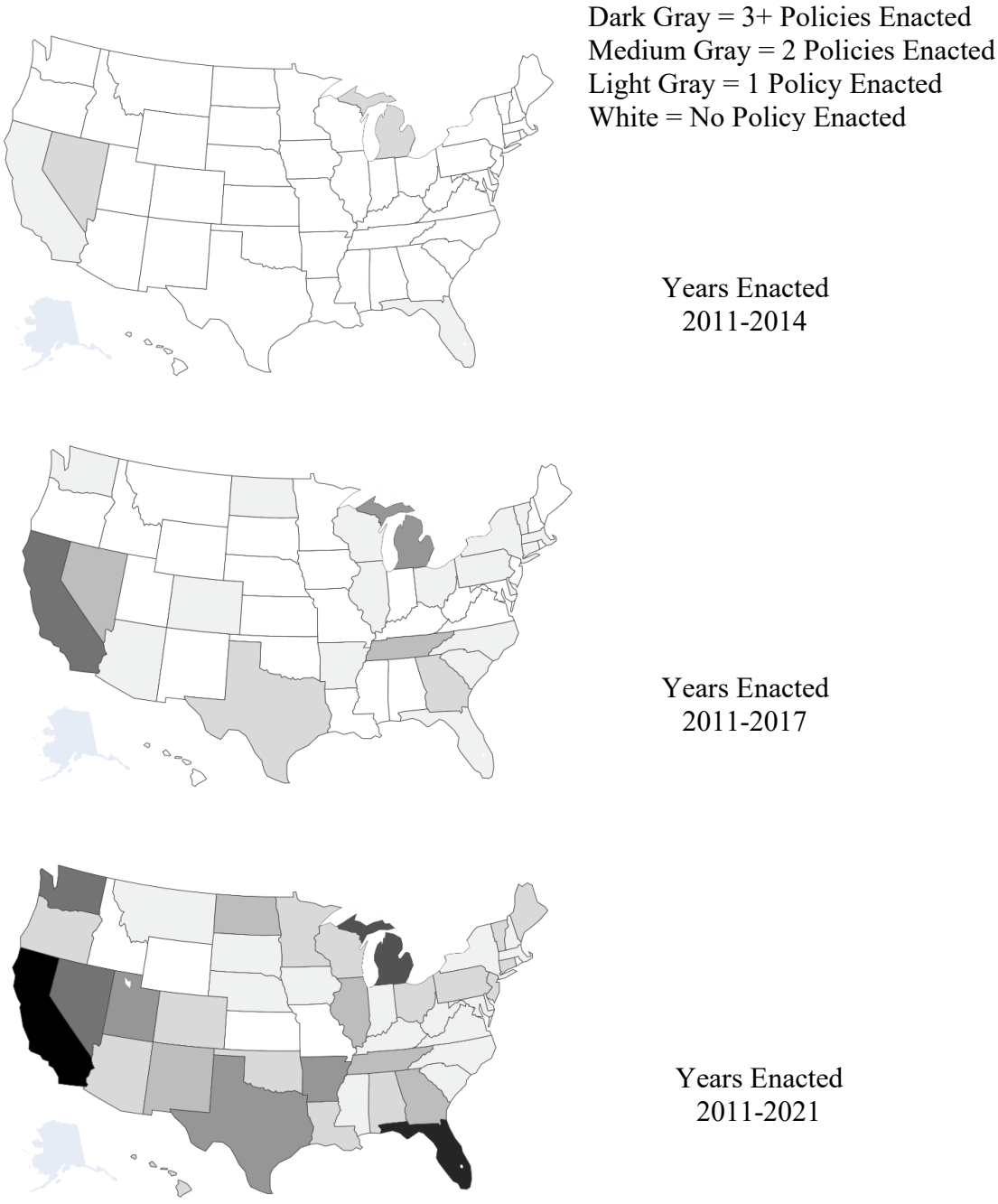


Figure 2.1 The Enactment of Autonomous Vehicles Regulations in the U.S. (2011-2021)

Figure 1 demonstrates AV policy adoptions over time. The diffusion of AV regulations across U.S. states has been gradual, uneven, and fragmented, offering rich variation for empirical analysis. Nevada became the first state to enact AV legislation in 2011, authorizing the testing of autonomous vehicles on public roads. In the years that followed, states adopted a wide range of regulatory approaches, resulting in a tapestry of laws that differ in both timing and substance. By 2021, 41 states had passed at least one AV-related law, yet the scope, depth, and regulatory orientation of these laws varied considerably. This staggered and differentiated adoption process makes AV policy an ideal case for studying how interstate competition influences not just the likelihood of adoption, but the specific content and direction of policy innovation over time.

2.5 Methodology

2.5.1 Data

I collect data from the National Conference of State Legislatures (NCSL) to compile a comprehensive dataset on state-level autonomous vehicle (AV) legislation. Developed by legal experts using LexisNexis StateNet, this dataset spans the years 2011 to 2021 and includes detailed information on each bill's state of origin, date of last legislative action, status (enacted, failed, or pending), sponsoring authors, bill summaries, assigned topics, and legislative history. In total, I retrieved 441 bills introduced across 48 states[3]. Of these, 112 bills originating from 41 states were successfully enacted. The NCSL categorizes each bill into one or more of 14 substantive topics, including licensing, testing, liability, and cybersecurity. On average, each bill is associated with three distinct topics. I use these topic assignments to analyze patterns of policy convergence and divergence.

[3] Alaska and Hawaii were excluded because their geographic isolation and policy context make them unsuitable for analyzing interstate competition dynamics.

To measure interstate competition, I construct a network based on labor mobility using Job-to-Job Flows (J2J) data from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program. The J2J data provide quarterly estimates of worker transitions across state labor markets, disaggregated by industry sector. This enables me to track the flow of workers between states over time and by sector, allowing for the construction of a dynamic, weighted network of labor-based economic ties. This network serves as the empirical foundation for my measure of competition in the knowledge economy.

I also collect data to operationalize regulatory capacity and to include relevant control variables. Academic expertise is measured using publication data from the Web of Science Core Collection, where I use keyword searches (e.g., "autonomous vehicle," "self-driving car") to identify peer-reviewed articles by author affiliation and year. Political expertise is proxied by legislative professionalism, using Squire's Index of State Legislative Professionalism (Squire 2017), which provides standardized scores across states. Additional controls include industry composition and population characteristics drawn from the U.S. Census Bureau's American Community Survey (ACS) and the Bureau of Labor Statistics (BLS), including annual sectoral employment shares. Information on partisan control of state government is obtained from the NCSL and verified with the Book of the States.

2.5.2 Analytical Strategies

This study employs two complementary analytical strategies to test the proposed hypotheses. The first focuses on policy adoption, while the second examines policy convergence and divergence over time.

To test policy adoption model, I use discrete-time event history analysis (EHA). This method is well suited for modeling the timing of first adoption events and has been widely

applied in the policy diffusion literature (Berry and Berry 1990; Boehmke 2009; Vasseur 2014). The unit of analysis is the state-year, covering the period from 2011 to 2021. Once a state enacts its first autonomous vehicle (AV) regulation, it is removed from the risk set in subsequent years. This allows the model to estimate the probability that a state adopts its first AV policy in a given year, conditional on not having done so previously.

To test whether competition leads to convergence or divergence in regulatory content, I adopt a dyadic modeling strategy. This approach models the similarity in policy topics between a pair of states (A and B) over time, using all recurring enacted bills rather than limiting the analysis to first adoption. The unit of analysis is the state dyad-year, capturing how state A's enacted AV bills relate to the prior policy profile of state B. This dyadic structure enables the analysis of directional convergence or divergence, and the role of moderating factors such as regulatory expertise (Gilardi and Füglister 2008; Shipan and Volden 2013; Volden et al. 2008).

2.5.3 Variables

Dependent Variables

This study employs different dependent variables for each analytic strategy. For the policy adoption model, the dependent variable is the first year in which a state enacts any autonomous vehicle (AV) legislation. This approach focuses on the initial regulatory response and aligns with common practices in event history analysis (Boehmke 2009). The variable is coded as 1 in the year a state first enacts an AV-related bill, and 0 otherwise, with states exiting the risk set after their first enactment.

To analyze topic-level convergence and divergence among competing states, I adopt the measurement approach developed by Shipan and Volden (2013), which assesses the extent to which a focal state's regulatory content aligns with or deviates from the topic profiles of other

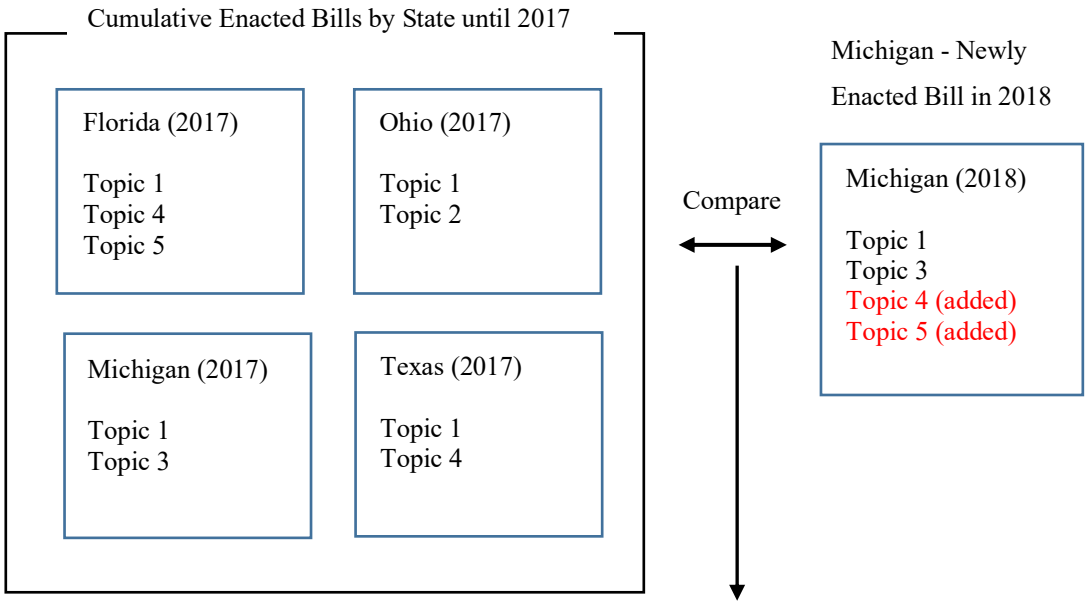
states in a given year. These directional shifts are coded as either convergence or divergence. Topic profiles are constructed based on 14 distinct dimensions of AV regulation categorized by NCSL legal experts. Table 2.1 summarizes these dimensions, highlighting the multidimensional nature of the policy space. Topics such as AV definitions, public road operation, and vehicle testing appear most frequently, reflecting the foundational concerns that dominate early regulatory efforts.

Table 2.1 Introduced and Enacted Bills by Topics

Topics	Introduction	Enacted
Definitions	181	38
Operation on Public Roads	151	36
Vehicle Testing	137	32
Operator Requirements	73	13
Insurance and Liability	90	13
Licensing and Registration	52	4
Commercial	67	26
Request for Study	69	15
Infrastructure and Connected Vehicles	37	14
Cybersecurity, Privacy, Wireless	28	2
Vehicle	15	4
Economic	5	4
Training	3	0
Emission	2	1

When a state enacts a bill in year t, I extract the topics associated with that bill and compare them to the cumulative topics adopted by each of the other 47 states through year t–1. If a newly enacted topic in the focal state has already been adopted by a comparison state, it is

considered a case of convergence. If the topic is not present in the comparison state's profile, it is considered a divergence. The number of converging and diverging topics are then aggregated to produce a net convergence score for each state dyad in each year. A positive score indicates that the focal state moved closer to the comparison state in terms of regulatory content; a negative score indicates divergence; and a score of zero indicates no net change in similarity.



State 1	State 2	Year	Cumulative Topic until 2017 (State 2)	Newly Added Topic in 2018 (State 1)	Direction
Michigan	Florida	2018	1, 4, 5	4, 5	+2
Michigan	Ohio	2018	1, 2	4, 5	-2
Michigan	Texas	2018	1, 4	4, 5	+1 -1 = 0

Figure 2.2 Diagram of Measuring Topic Convergence in Dyadic Level

To illustrate the measurement approach, consider the example in Figure 2.2. In 2018, Michigan enacted two new topics, topic 4 and topic 5. Florida's cumulative regulatory profile through 2017 included topics 1, 4, and 5. Since both newly enacted Michigan topics matched those in Florida's existing profile, Michigan's movement toward Florida is scored as +2. By contrast, Ohio had adopted topics 1 and 2 through 2017, so Michigan's new topics did not

overlap with Ohio's, resulting in a score of –2. Texas had adopted topics 1 and 4, so Michigan's topic 4 matched while topic 5 did not, resulting in a net score of zero. This comparison is repeated for all dyads across all years in the dataset.

These net convergence scores are then transformed into a binary dependent variable. If the score is greater than zero, meaning the focal state became more similar to the comparison state in that year, the dyad is coded as 1. Otherwise, it is coded as 0. This binary variable is then used as the dependent variable in a dyadic logistic regression model, which estimates the likelihood of convergence as a function of network-based measures of economic competition, as well as relevant controls.

Independent Variables

The central independent variable in this study is interstate economic competition, operationalized through two network-based measures: direct competition and indirect competition (measured as structural equivalence). Both constructs are derived from the U.S. Census Bureau's Job-to-Job (J2J) worker flow data, which track the movement of individual workers across state boundaries over time. These data allow for the construction of a dynamic labor mobility network, capturing how states are connected through the flows of skilled labor, a key resource in the knowledge economy.

This network-based approach offers a more nuanced understanding of competition than traditional geographic measures (e.g., state contiguity or shared economic regions), which often assume that states primarily compete with their physical neighbors. By contrast, labor mobility data allow us to capture functional competitive relationships: states compete with others that attract the same types of workers, regardless of physical proximity. In the context of autonomous vehicle (AV) regulation, where the attraction and retention of high-skilled workers and tech

firms are central to economic strategy, this labor-based conceptualization of competition is both substantively meaningful and theoretically grounded.

Figure 3 provides a visual illustration of these two types of competition within the labor mobility network. The first diagram shows direct competition, in which states like Texas, New York, and Georgia are significant competitors to Michigan because they receive a high volume of outbound workers from Michigan. This suggests that Michigan is directly losing labor to these states, and therefore likely perceives them as rivals in attracting and retaining human capital. The magnitude of these flows also reflects the intensity of competition, for example, New York is a stronger competitor than Georgia if it draws a larger proportion of Michigan's workforce.
The second diagram illustrates indirect competition, captured through structural equivalence. This form of competition is based not on direct interaction, but on similarity of position within the labor mobility network. For instance, if both Michigan and Wisconsin tend to attract workers from the same third-party states (e.g., California or Illinois), they occupy comparable network positions, even if they do not exchange workers with each other directly. This implies a form of latent competition, where states in structurally equivalent positions are exposed to similar pressures and constraints. While they may not monitor each other directly, they are operating under shared strategic conditions and thus may behave similarly in regulatory decisions.
These two measures, direct and indirect competition, capture distinct but interrelated mechanisms of competitive influence. The former reflects dyadic, zero-sum competition between states, while the latter reflects field-level similarity, where structurally equivalent actors face comparable incentives to converge or differentiate in their regulatory strategies.

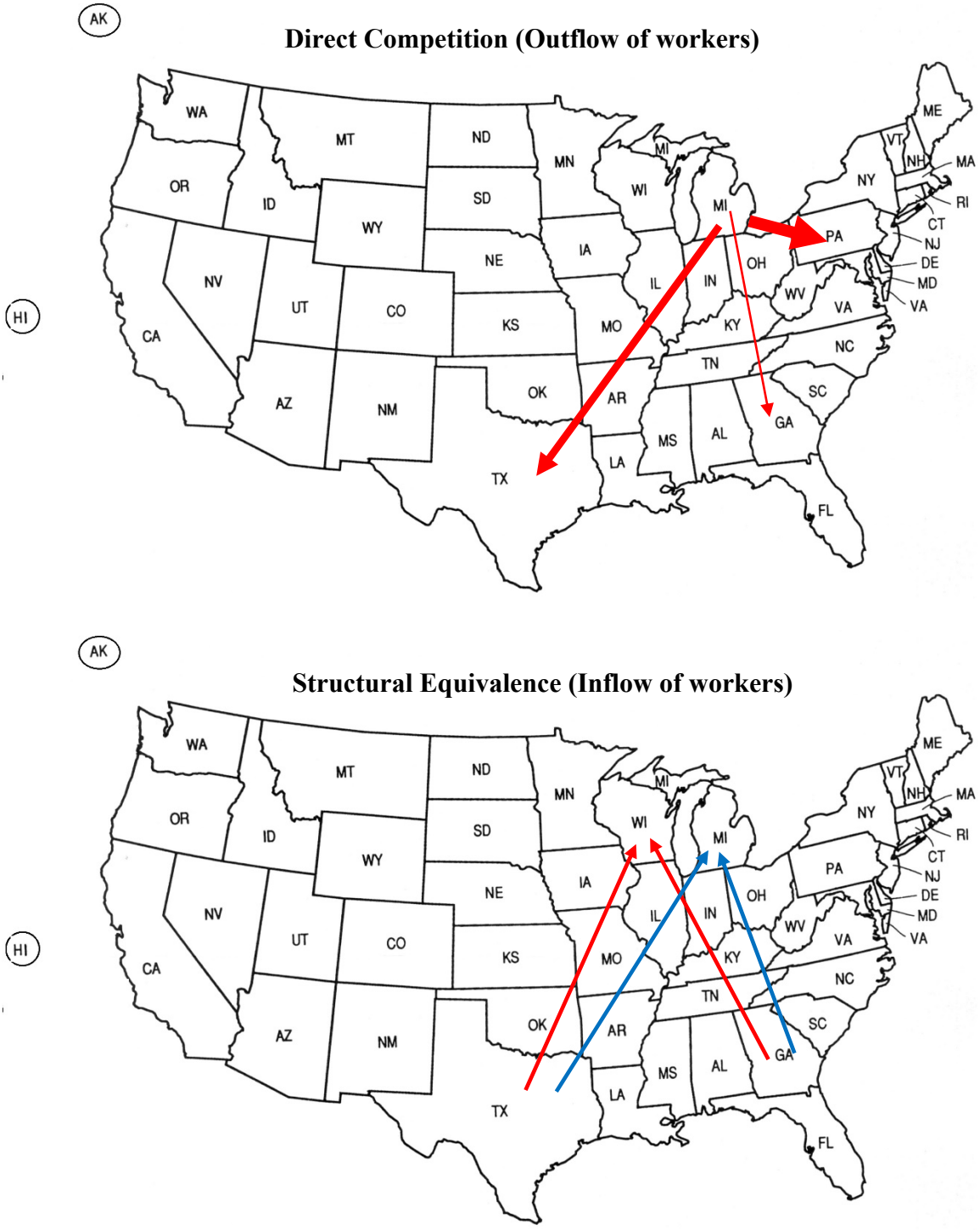


Figure 2.3 Labor Mobility and State Competition Measures

Direct competition

To capture direct competition, I measure the degree to which states are locked in dyadic, labor-market-based rivalries with one another. The underlying assumption is that states that experience significant outflows of skilled workers to other states are likely to perceive those destination states as competitors, particularly in automotive and tech industry domains.
The measure is constructed in two steps. First, I calculate the proportion of a focal state's total outbound workforce that moves to each other state in a given year. For each state pair (state i and state j), this is expressed as:

$$Intensity\ of\ Labor\ Outflow_{it} = \left(\frac{Worker\ Move_{ijt-1}}{Total\ Worker\ Move_{it-1)}}\right)^2$$

This proportion reflects the intensity of labor outflow from state i to state j, and therefore the extent to which state i is likely to be exposed to j's competitive influence.

Second, I multiply this squared proportion by the number of AV-related bills enacted by the receiving state j in the previous year. Squaring the proportion increases the relative weight of strong labor connections, allowing the measure to more heavily reflect policy influence from states with especially high worker draw. The full index is calculated as follows:

$$Direct\ Competition\ Effect_{it} = \sum_j \left(AV\ Bills_{jt-1}\right)\ X\ \left(\frac{Worker\ Move_{ijt-1}}{Total\ Worker\ Move_{it-1)}}\right)^2$$

This produces a continuous measure for each state-year indicating the cumulative policy influence of its strongest direct competitors, based on recent labor outflows and those competitors' AV legislative activity. It reflects the idea that states are more likely to respond to regulatory actions by states that pose real competitive threats in attracting labor and firms.

Structural Equivalence

To measure indirect competition, I calculate the structural equivalence between states in the labor mobility network. Structural equivalence reflects the degree to which states share similar positions within the network, which means they compete for the same third-party labor flows, even if they do not interact directly. Two states may not send workers to one another but may both attract workers from the same set of innovation hubs (e.g., California, Texas), suggesting shared constraints and strategic pressures.

For example, if both State A and State B attract workers from the tech industry in State C, they occupy similar positions in the labor mobility network. This indicates that they are functionally equivalent in terms of the types of workers they attract and the states they draw from, even if they do not directly exchange labor with one another. Such structural similarity suggests that they face comparable economic pressures and may be inclined to adopt similar policy strategies or diverge policy contents.

To operationalize structural equivalence, I construct a matrix that captures the distribution of incoming workers to each state from all other states, disaggregated by industry. For each state, this generates a vector profile that reflects which types of workers (by industry) are entering the state and from where. I focus specifically on inflows, rather than outflows, because AV regulation is fundamentally about attracting talent, firms, and investment. States compete not simply to retain workers, but to position themselves as destinations for high-skilled labor in emerging technology sectors. Thus, inflows provide a more accurate reflection of a state's position within the national labor competition field.

Using these industry-specific inflow profiles, I then compute Pearson correlation coefficients between each pair of states. This yields a structural equivalence matrix capturing the degree of similarity in labor market positioning. A high correlation between two states' inflow

profiles indicates that they tend to draw workers from similar origin states and in similar sectors, implying that they are structurally equivalent competitors in the labor market. Conversely, low correlations suggest that the states attract distinct kinds of workers or from different sources, reflecting divergent competitive positions.

This approach aligns with classical definitions of structural equivalence in network theory (Burt 1987), where equivalence is determined not by direct ties but by similar patterns of relationships to third parties. In this context, it reveals latent competition among states that are targeting and attracting the same kinds of talent, even if they are not in direct labor exchange with one another.

I then multiply the structural equivalence score between state i and state j by the number of AV-related bills enacted in state j in the previous year. This weighting assumes that structurally equivalent states are more likely to respond to policy developments in other similarly positioned jurisdictions. The resulting formula is:

$$Indirect\ Competition\ Effect_{it} = \sum_{j} \left(AV\ Bills_{jt-1}\right)\ X\ \left(Structural\ Equivalence_{ijt-1}\right)$$

Regulatory Capacity

To account for variation in states' ability to respond to competitive pressures with complex policy responses, I include measures of regulatory capacity, focusing on two key dimensions: academic expertise and political expertise. These measures capture different facets of a state's institutional ability to formulate, evaluate, and implement regulations related to emerging technologies such as autonomous vehicles (AVs).

Academic Expertise

Academic expertise reflects a state's epistemic capacity, its access to domain-specific knowledge and its ability to generate or evaluate policy ideas informed by technological understanding. Given the technical complexity of AV regulation, states with greater exposure to academic research in this area are likely to have stronger regulatory capabilities, whether through in-house analysis or engagement with local universities, research centers, or epistemic communities (Haas 1989).

To operationalize this, I constructed a time-varying measure of academic expertise based on the number of academic publications related to autonomous vehicles produced within each state annually. I extracted publication data from the Web of Science Core Collection, using keyword searches for "autonomous vehicle," "self-driving car," "robotic car," and "driverless car." I then geocoded the institutional affiliations of authors to assign each publication to a state. This procedure allowed for a consistent, replicable indicator of AV-related academic activity at the state level over time. To address skew in the distribution of publication counts, since a small number of states produce the majority of articles, I applied a logarithmic transformation to normalize the values. The resulting variable provides a continuous indicator of each state's yearly academic capacity in AV-related domains.

Political Expertise

Political expertise reflects the institutional professionalization of state legislatures, which influences a state's ability to process complex information, draft technically nuanced legislation, and act independently of external policy templates. Following existing literature in state politics, I use Squire's Index of Legislative Professionalism (Squire 2017), a widely used and validated measure of legislative capacity.

Squire's index incorporates multiple components: legislative salary, staff size, and session length. Higher scores reflect legislatures that are more professionalized, meaning they have greater resources, more policy support, and more time to deliberate. Such legislatures are better positioned to assess emerging technologies, consult with experts, and craft regulations that diverge from standard policy templates. This variable is time-invariant for this study, as I use the most recent available version of the Squire index, which reflects structural characteristics of legislatures that change relatively slowly over time.

Control Variables

To isolate the effects of competition and regulatory capacity, I include a set of control variables commonly used in policy diffusion research. For the policy adoption models, I account for both spatial and structural influences. Geographic contiguity is included as a binary variable indicating whether a state shares a border with another state that has adopted AV-related legislation. I also include a variable identifying whether two states belong to the same Bureau of Economic Analysis (BEA) economic region, capturing the potential influence of regionally shared economic conditions. To control for industrial characteristics relevant to AV policy, I include two continuous measures: the proportion of a state's workforce employed in the technology sector and the proportion employed in the auto manufacturing sector. These variables help account for the underlying economic relevance of AV regulation to each state's labor market.

Political context is captured using a binary variable indicating whether a state has unified or divided government control, a common indicator of legislative alignment in policy diffusion studies. To capture each state's embeddedness within the broader labor mobility network, I include degree centrality as a measure of general network exposure. Finally, I control for the

presence of a federal policy signal by including a dummy variable coding all years after 2016 as 1, reflecting the release of formal guidance on AV policy by the U.S. Department of Transportation. This variable accounts for a potential shift in national attention to AV governance that may have influenced state-level activity.

In the dyadic convergence/divergence models, I include relational controls that reflect differences between state pairs. These include the absolute difference between states in the proportion of workers employed in the auto and tech sectors, which captures industrial dissimilarity that may affect convergence. I also control for population difference between states, which may proxy for asymmetries in administrative capacity, visibility, or political influence. Lastly, I include a binary variable indicating whether the two states share the same political party in control of government, which may facilitate alignment in policy orientation and regulatory content (Shipan and Volden 2013; Volden 2008)

2.6 Results

Table 2.2 presents pairwise correlations among variables used in the state-level enactment analysis. Notably, the network-based competition measures, structural equivalence and direct competition, are only weakly correlated with enactment, which helps alleviate concerns about multicollinearity in the multivariate models. Structural equivalence and direct competition are moderately correlated with each other, suggesting that while they both capture network-based competition, they reflect distinct mechanisms: the former represents similarity in competitive position, while the latter captures actual labor mobility between states. Both measures are only weakly correlated with standard proxies for interstate competition, such as geographic contiguity and BEA economic areas, underscoring that the network-based approach captures a substantively different dimension of rivalry. This distinction reinforces the theoretical

Table 2.2 Descriptive Statistics: Correlation Matrix for Enactment Model

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Enactment	1												
2. Structural Equivalence	.079	1											
3. Direct Competition	-.038	.033	1										
4. Neighborhood	-.002	.021	.264	1									
5. BEA (Economic Base)	.137	-.045	-.059	-.112	1								
6. Centrality	-.026	.084	-.318	-.019	-.029	1							
7. Academic Expertise	-.017	-.102	-.108	-.098	.033	-.189	1						
8. Political Expertise	.210	-.090	.223	-.200	.089	-.557	.359	1					
9. Tech Proportion	-.036	.004	.796	.328	-.163	-.077	-.031	.065	1				
10. Auto Proportion	-.033	.042	.572	.246	-.142	.116	-.101	-.099	.717	1			
11. Party Control	.083	.081	-.119	-.031	-.073	-.144	.175	.168	-.073	-.198	1		
12. Federal	.210	-.144	.116	-.015	-.008	-.227	.063	.502	.068	.020	.038	1	
13. Year	.324	-.084	.045	-.249	.155	-.009	.028	.440	.052	.035	.004	.664	1

Table 2.3 Descriptive Statistics: Correlation Matrix for Dyadic Model

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Movement	1												
2. Structural Equivalence	.077	1											
3. Direct Competition	.042	.133	1										
4. Neighborhood	-.017	.003	.246	1									
5. BEA (Economic Base)	.076	-.114	-.164	-.125	1								
6. Centrality	.136	.154	-.236	-.105	.052	1							
7. Academic Expertise	-.171	-.158	-.167	-.126	-.001	-.265	1						
8. Political Expertise	.021	-.156	.007	-.281	.073	-.581	.475	1					
9. Party Control	.039	.067	.824	.230	-.230	-.153	-.046	-.018	1				
10. Auto Difference	.096	.219	.614	.246	-.167	.174	-.201	-.190	.685	1			
11. Tech Difference	.011	.011	-.113	-.047	-.115	-.204	.186	.169	.014	-.082	1		
12. Population Difference	-.041	-.041	.044	-.046	.077	.051	-.229	.023	.055	.014	.009	1	
13. Same Political Party	-.043	-.043	.043	-.245	.206	-.076	.020	.449	.023	-.018	.064	.409	1

motivation for moving beyond traditional geographic indicators to capture economically meaningful relationships in a mobile, knowledge-based economy. Additionally, direct competition shows a strong correlation with tech and auto industry proportions, suggesting that labor flows are closely tied to industrial composition in sectors central to AV development.

Table 2.3 displays the correlation matrix for dyadic-level variables used in analyzing topic convergence and divergence. Movement which reflects policy alignment across dyads is weakly and positively correlated with both structural equivalence and direct competition, indicating that states in competitive or structurally similar positions tend to show slight alignment in policy topics. A notable correlation appears between direct competition and party control and auto industry difference, suggesting that partisan alignment and industrial similarity might underpin certain patterns of competitive convergence. Academic and political expertise exhibit moderate negative correlations with both structural equivalence and direct competition, implying that more expert states are potentially less entangled in these competition-based relationships, consistent with later findings about divergence.

2.6.1 Policy Adoption Model

Table 2.4 presents the EHA models aimed at estimating the probability of AV bill enactment. Model 1 displays the coefficients from the control variables in the analysis. It reveals that the proportion of technology industry workers within a state has a positive relationship with the likelihood of AV bill enactment, a significant effect that holds across all the models. This suggests that states with a greater concentration of technology industry workers are more inclined to develop AV regulations. Another control variable that exhibits statistical significance is the federal action dummy variable. Since 2016, when the federal government announced

Table 2.4 Logistic Regression on Enactment of Autonomous Vehicle Bills

VARIABLES	(1) Baseline	(2) Neighbor	(3) BEA	(4) Network	(5) Full
Structural Equivalence				3.203***	4.230***
				(1.070)	(1.390)
Direct Competition				2.103**	1.742**
				(1.252)	(1.129)
Neighborhood		0.456			-1.752
		(0.797)			(1.287)
BEA (Economic Base)			1.371		0.184
			(0.865)		(1.315)
Centrality	0.0403	0.0441	0.0256	0.0755	0.0767
	(0.157)	(0.180)	(0.157)	(0.162)	(0.194)
Publication	-1.215	-2.142	-1.058	-1.370	-2.331
	(2.990)	(4.027)	(3.011)	(3.046)	(4.718)
Tech Industry Proportion	4.337***	4.859***	4.265***	4.536***	4.813***
	(1.601)	(1.709)	(1.608)	(1.635)	(1.686)
Auto Industry Proportion	-0.931	-0.316	-1.039	-1.246	0.0233
	(1.909)	(2.001)	(1.961)	(1.921)	(2.078)
Professionalism	-0.0696	-0.212	-0.149	-0.151	-0.412
	(0.521)	(0.589)	(0.587)	(0.580)	(0.607)
Academic Expertise	0.537	1.719	0.737	1.040	1.496
	(1.543)	(1.745)	(1.631)	(1.630)	(1.783)
State Control (Divided)	-0.124	0.482	-0.0192	0.210	0.693
	(1.008)	(1.148)	(1.047)	(1.063)	(1.191)
Federal Action (after 2016)	5.359***	7.235***	5.640***	6.119***	7.315***
	(1.412)	(1.781)	(1.495)	(1.600)	(1.811)
Year	2.122**	2.976**	1.933	2.215*	2.721**
	(0.990)	(1.270)	(1.228)	(1.212)	(1.319)
Year Squared	-0.0225	-0.181*	-0.0207	-0.0667	-0.168
	(0.0630)	(0.0968)	(0.0838)	(0.0854)	(0.103)
Constant	1,653***	2,060***	1,706***	1,737***	2,031***
	(439.0)	(504.4)	(467.6)	(455.5)	(524.3)
R-Squared	0.2151	0.2211	0.2195	0.2512	0.2641
Observations	340	340	340	340	340

*** p<0.001, ** p<0.01, * p<0.05

guidelines for autonomous vehicles, state policymakers have been more active in developing AV regulation bills.

Models 2 and 3 introduce traditional measures of interstate competition, geographic contiguity and shared economic regions (BEA areas) that are commonly used in diffusion research. However, neither measure shows a statistically significant relationship with policy adoption. The geographic contiguity coefficient is small and non-significant, and turns negative when included alongside other measures. Likewise, shared economic base (BEA) has no meaningful association with adoption likelihood. These null results are methodologically significant: they call into question the assumption that proximity indicates the competitive relationship. Instead, these findings suggest that states are not simply copying neighbors or regional peers; rather, they may be responding to more nuanced, structural forms of competition. Models 4 and 5 test this possibility by incorporating two network-based competition measures used in this study: structural equivalence and direct competition based on labor mobility networks. Both variables yield positive and statistically significant coefficients, providing strong support for Hypothesis 1, which posits that competitive pressures, properly conceptualized in relational labor-market terms, increase the likelihood of AV policy adoption. In Model 5, the coefficient for structural equivalence is 3.203 ($p < 0.001$), and for direct competition it is 2.103 ($p < 0.01$). These effects persist even in the full model (Model 6) where other standard competition measures are included as control variables.

The robustness of these effects, even after controlling for conventional competition measures, demonstrates the empirical utility of the network-based framework introduced in this paper. These findings indicate that competitive pressures in a knowledge-based economy are not merely spatial or regional; they are relational, operating through labor mobility and structural

positions within national economic networks. In short, states are more likely to adopt AV policies when they are structurally similar to, or in direct labor-market competition with, other states that have already enacted such policies.

2.6.2 Policy Convergence and Divergence Model

Table 2.5 examines how interstate competition influences the content of autonomous vehicle (AV) regulation, focusing on whether states adopt similar topics as their competitors (policy convergence) or instead pursue distinct regulatory topics (policy divergence). A positive coefficient indicates that State A is aligning with the topics already present in State B's policy profile, while a negative coefficient indicates that State A is introducing novel topics absent in State B's portfolio.

Model 1 presents the baseline dyadic specification including control variables only. Most notably, conventional competition measures, such as geographic contiguity (i.e., whether states are neighbors) and BEA economic area affiliation, do not show statistically significant effects on policy convergence. This is a critical finding because relying only on these standard proxies would incorrectly suggest that competition has little influence on regulatory alignment. Several control variables do show significant associations with convergence and divergence. States are more likely to converge when they share partisan control, supporting the idea that ideological alignment encourages policy emulation (Shipan and Volden 2013). Similar industrial profiles, especially in auto and tech sectors, also predict convergence, suggesting shared economic challenges prompt similar policy responses (Cao and Prakash 2012). Conversely, greater population differences predict divergence, possibly reflecting the greater capacity or autonomy of larger states, or the tendency of smaller states to follow larger peers.

Table 2.5 Logit Analysis of the Probability that State A moves toward State B on Bill Topic

	(1) Baseline	(2) Competition	(3) Political Expertise	(4) Academic Expertise
Structural Equivalence		0.934***	-2.472	0.723
		(0.256)	(2.321)	(0.480)
Structural Equivalence X Political			0.401	
			(0.273)	
Structural Equivalence X Academic				0.092
				(0.206)
Direct Competition		-1.422	2.066	3.447
		(1.456)	(11.221)	(2.557)
Direct Competition X Political			3.074	
			(1.353)	
Direct Competition X Academic				-2.404*
				(1.086)
Regional Relations				
Neighbor	0.219	0.211	0.254	0.258
	(0.232)	(0.237)	(0.230)	(0.238)
BEA (Similar Economic Base)	0.243	0.172	0.183	0.185
	(0.289)	(0.281)	(0.283)	(0.282)
State A Characteristics				
Centrality	0.411	0.444*	0.419	0.463*
	(0.213)	(0.200)	(0.252)	(0.202)
Academic Expertise	0.009	-0.010	0.006	0.034
	(0.147)	(0.140)	(0.144)	(0.140)
Political Expertise	0.786	0.787	0.771	0.823
	(0.940)	(0.906)	(0.927)	(0.927)
State Control (Divided)	1.155***	1.152***	1.148***	1.164***
	(0.304)	(0.312)	(0.318)	(0.317)
Interstate Relations				
Auto Industry Difference	0.138***	0.133***	0.133***	0.135***
	(0.030)	(0.031)	(0.031)	(0.031)
Tech Industry Difference	0.093**	0.091**	0.089*	0.088**
	(0.034)	(0.035)	(0.035)	(0.034)
Population Difference	-1.578***	-1.583***	-1.613***	-1.638***
	(0.180)	(0.197)	(0.207)	(0.208)
Same Political Party	0.487**	0.472**	0.485***	0.489***
	(0.153)	(0.149)	(0.147)	(0.147)
Constant	-5.706***	-6.085***	-5.885**	-6.362***
	(1.501)	(1.385)	(1.922)	(1.474)
Year Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.1428	0.1475	0.1495	0.1495
Observations	3,570	3,570	3,570	3,570

*** p<0.001, ** p<0.01, * p<0.05

Model 2 introduces the key theoretical variables structural equivalence and direct competition, each capturing a distinct form of competitive pressure. Structural equivalence, which captures whether two states occupy similar positions in the broader labor mobility network, is positively and significantly associated with convergence ($\beta = 0.934$, $p < .001$). This finding supports Hypothesis 2-1 and aligns with Burt's (1987) theory of structural equivalence, which posits that actors in similar structural positions, those facing comparable constraints and opportunities, tend to adopt similar strategies. In this case, states that are not necessarily exchanging workers directly but are exposed to similar competitive pressures from third-party states are more likely to converge in AV regulation topics.

In contrast, direct competition, which captures bilateral labor mobility between states, does not exhibit a significant main effect. This null result is noteworthy: while states engaged in direct competition might be expected to align their policies, the result suggests that convergence is not a uniform response to competitive pressure. It invites the possibility that states may instead respond to direct competition through differentiation, especially when resources for innovation are available.

Models 3 and 4 test conditional effects of regulatory capacity. Model 3 examines the moderating role of political expertise, measured by legislative professionalism. While the interaction terms for both structural equivalence and direct competition are in the expected directions (positive for convergence), neither is statistically significant, offering little support for Hypothesis 3-2. This implies that variation in legislative professionalism does not significantly alter how states respond to competitive pressures when it comes to policy content. This is likely due to the knowledge-intensive nature of AV regulation: while politically professionalized states

may be better at processing routine policy, they may still lack the substantive technical knowledge required to generate innovative regulation in complex, fast-evolving domains. Model 4 formally tests this idea by introducing interaction terms between competition and regulatory capacity, particularly academic expertise, to evaluate Hypothesis 3-1. The interaction between direct competition and academic expertise is statistically significant and negative ($\beta = -2.404$, $p < .05$), indicating that the effect of direct competition on convergence becomes more negative as a state's academic expertise increases.

Substantively, this means that states engaged in direct competition tend to converge with their rivals when they lack expertise, but diverge from their rivals when they have strong academic capacity. This confirms Hypothesis 3-1 and supports the broader theoretical claim that divergence is a capacity-dependent strategy (Bromley-Trujillo and Karch 2021; Haas 1989). As shown in Figure 2.4, the predicted probability of convergence under direct competition is high when publication counts are low, but drops sharply as academic expertise increases.

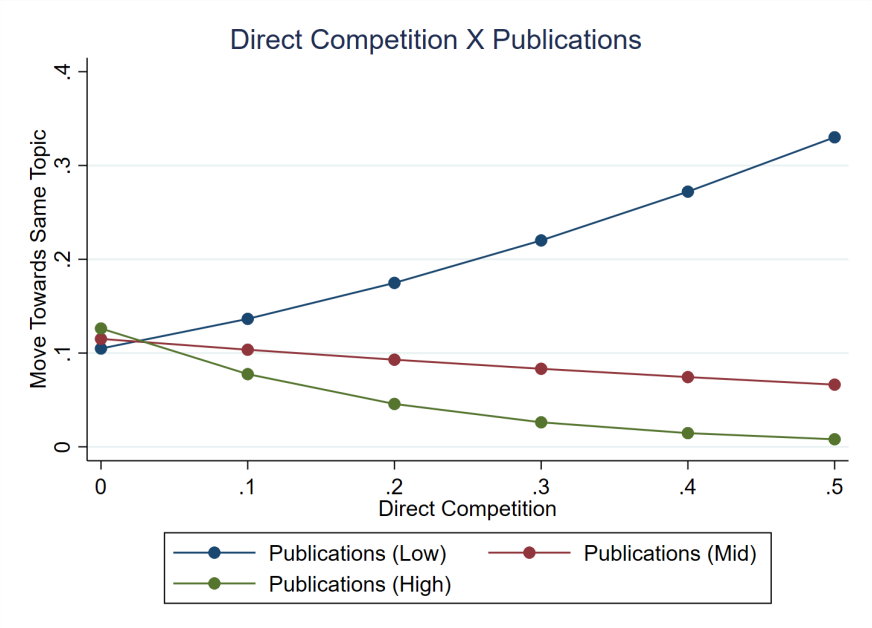


Figure 2.4 Direct Competition Effect Conditional on Academic Expertise

This interaction result reinforces the idea that divergence is not a default response to direct competition, it must be enabled by epistemic resources. Crafting novel regulatory responses in an emerging and uncertain domain like AV governance requires not only the strategic desire to differentiate but also the expertise to define and defend an alternative approach. States lacking this expertise may find imitation to be the safer and more administratively feasible strategy.

The lack of a significant interaction between academic expertise and structural equivalence suggests that indirect competition (via structural similarity) induces convergence regardless of expertise level. This is consistent with the idea that convergence under structural equivalence is driven by parallel adaptation rather than deliberate observation or rivalry. States in similar structural positions respond similarly to shared environmental conditions (Mizruchi 1990; White 1981), so their convergence does not require advanced internal capacity.

Taken together, these results suggest a dual mechanism in how competition influences policy content. Structural similarity leads to emulation and convergence, especially when uncertainty is high. However, direct competition prompts differentiation when states possess internal knowledge capacity to pursue novel regulatory paths. These findings underscore the importance of considering both relational structures and endogenous capacities when analyzing the diffusion of complex and innovation-driven policies.

2.7 Discussion

In conclusion, this study has demonstrated how interstate competition shapes both policy adoptions and contents of technology regulations. First, I found that competitive pressure which is measured through labor mobility networks increases the likelihood of AV bill adoptions. Both direct competition and structural equivalence remain significant even when controlling for

conventional measures. Second, the two types of competition show distinct patterns in shaping policy content. Structural equivalence leads to policy convergence but shows no interaction with regulatory capacity, suggesting that similarly positioned states tend to align regardless of internal expertise. In contrast, direct competition on its own does not drive convergence or divergence, but when paired with high academic expertise, it predicts divergence. This indicates that regulatory capacity, particularly in the form of epistemic resources, enables some states to pursue distinct regulatory paths. Political expertise, measured via legislative professionalism, does not exhibit any moderating effects.

A notable finding from this study is the significance of network-based approach to measuring interstate competition. While network-based competition measures show consistent and significant effects, models that include standard competition measures such as geographic contiguity and shared economic base (BEA) reveal no significant competitive influence. This indicates that, in a knowledge economy, where skilled labor and firms are highly mobile, competition is structured less by geographical proximity than by talent flows and shared market space. The network approach provides a more accurate and contextually grounded lens for understanding how states compete, particularly in complex, high-tech policy domains. This underscores the importance of developing competition measures that are not only theoretically informed but also aligned with the specific mechanisms and dynamics at work in each policy area. Rather than relying on one-size-fits-all proxies, future diffusion research should adopt innovative, context-sensitive approaches that reflect how competition operates across different regulatory and economic environments.

Direct Competition vs Structural Equivalence

An important finding from this study is that even among network-based measures of competition, structural equivalence and direct competition produce different patterns of policy diffusion. While both metrics capture competitive relationships embedded in labor mobility networks, they reflect qualitatively distinct relational logics. Structural equivalence predicts policy convergence, while direct competition has no main effect unless moderated by academic expertise. The different effects suggest that it is critical to distinguish the nature of competition implied by the network structure, and to interpret convergence or divergence outcomes not as generic responses to "competition," but as contingent on the type of competitive relationship and the internal capacity of the state.

The convergence observed among structurally equivalent state pairs aligns with theories of institutional isomorphism and network-based diffusion. These states occupy similar positions in the labor mobility network, often competing for the same third-party workforce. Although these states may not monitor each other directly, they are nonetheless aware of one another as competitors in a shared strategic field. Because they are seen as substitutable by mobile firms and skilled workers, each has an incentive to maintain regulatory legitimacy. As Burt (1987) and White (1981) argue, structurally equivalent actors care about one another not through observation, but through shared dependence on common audiences. This indirect mutual awareness generates convergence, not necessarily because states copy each other, but because they face similar incentives, pressures, and reputational benchmarks. In such contexts, adopting widely accepted or "legitimate" regulatory topics becomes a rational and risk-averse strategy, consistent with the logic of mimetic isomorphism (DiMaggio and Powell 1983).

The absence of divergence among structurally equivalent states is also theoretically consistent. While these states compete in the abstract, vying for similar resources, they do not

engage in direct, zero-sum rivalries that typically incentivize differentiation. Without a clear rival to outmaneuver, the strategic pressure to stand out is weak. Moreover, we find no significant interaction between regulatory capacity and structural equivalence, suggesting that convergence is not driven by expertise but emerges from shared structural positioning. In this context, convergence appears to be a default, low-cost response which states adopt similar policies not because they intend to innovate, but because their network roles expose them to similar reputational and institutional pressures. This pattern aligns with institutional theory: in uncertain or evolving domains, states often conform to emergent norms as a way to signal legitimacy, regardless of their internal policy capacity (Bromley-Trujillo and Karch 2021; Meyer and Hollerer 2010).

By contrast, the significant interaction between direct competition and academic expertise supports the idea that divergence is a strategic but resource-intensive response to competitive pressure. In cases of direct competition, states are engaged in visible, zero-sum contests for skilled workers and industry investment. In such rivalrous relationships, mimicking a competitor may undermine a state's ability to stand out, making divergence a potentially valuable strategy. However, formulating distinctive, technically sound policies in a complex domain like AV governance requires high levels of epistemic capacity. Only states with substantial academic infrastructure and expertise are able to translate competitive pressure into innovative or differentiated policies. This aligns with theories of strategic differentiation (Deephouse 1999; Lieberman and Asaba 2006) and epistemic governance (Haas 1989), which emphasize that actors need not just motivation but also capability to break from the field. Thus, divergence under direct competition is not a universal response, but a selective one, pursued only by those with the internal resources to take risks and offer alternative regulatory visions.

These findings highlight a crucial point: competition is not a single, uniform mechanism, and its effects depend on how it is measured and conceptualized. Structural equivalence and direct competition, though both network-based, produce different outcomes because they capture different relational dynamics. This underscores the need for greater theoretical and methodological precision in competitive diffusion studies. Rather than relying on generic indicators, researchers must carefully align measures with the specific mechanisms of competition they seek to capture. Doing so will deepen our understanding of when and how competition drives policy convergence or divergence.

Implications

This study has several theoretical and policy implications. First, this study enhances our understanding of the role of competition on policy diffusion. A significant portion of competitive diffusion research has predominantly concentrated on investigating "race to the bottom" or "race to the top" arguments. Nevertheless, acknowledging policy convergence and divergence as outcomes of competition represents a noteworthy improvement (Carruthers and Lamoreaux 2016). This is particularly relevant in empirical terms when we consider the presence of multiple topics that can be developed within a single regulatory framework. This closely relates to the "invention" or "innovation" of regulations. As regulatory innovation increasingly accompanies technological innovation, understanding why some states imitate while others invent becomes a critical research agenda (Moses 2013).

Second, I have delved into the conditioning effects of competition on convergence and divergence dynamics. This aligns with the insights of prior research that underscore the importance of elucidating the conditioning factors that influence diffusion processes (Gilardi 2016; Mooney 2020). I found that regulatory capacity, particularly epistemic communities, plays

a significant role in influencing policymakers to either diverge or converge in this paper. Future research should examine how different forms of expertise, institutional resources, or policy legacies shape a state's ability to respond to competitive pressures, and whether similar mechanisms operate in other policy domains.

Third, this study offers a methodological contribution by advancing how we measure competition in policy diffusion. Whereas prior studies often relied on geographic proximity or shared economic regions (Graham et al. 2013; Cao 2012), I introduced network-based measures rooted in labor mobility flows to capture competitive relationships among states. This approach aligns more closely with the theoretical premise that states compete for skilled labor and industrial positioning in a knowledge economy. Given its broader applicability, this network-based measure offers a valuable tool for analyzing competition-driven diffusion in other areas of emerging technology regulation and beyond (Cao and Prakash 2010).

Lastly, my study has broader implications for understanding how competition is a mode of governance for regulating emerging technologies. This brings us a question of whether competitive coordination is feasible (Graham et al. 2013). One of the reasons I delved into the realms of policy convergence and divergence is to explore the potential for coordination across jurisdictions (Füglister 2012). Presently, the United States is, in its own manner, championing policy innovation and experimenting with regulations in various regions, akin to the concept of a "laboratories of democracy" (Volden 2006). It is possible that excessive divergence of policies across states might cause societal costs because engineers and businesses might have to deal with the varying regulations that do not match with their technologies. Consequently, competitive pressures may necessitate a form of coordination to ensure overall positive outcomes as a society. While I cannot immediately make judgments about the societal effects of competitive

diffusion, there may ultimately be a requirement for a guiding direction that integrates policies across states (Mooney 2020).

Limitation and Future work

While this study focuses on interstate dynamics, future research should explore how competitive diffusion unfolds across multiple governance scales. In particular, examining vertical interactions between federal and state governments, or horizontal diffusion involving international jurisdictions, could reveal how different layers of authority interact to shape technology regulation. As emerging technologies increasingly raise trans-jurisdictional challenges, understanding how competitive, collaborative, and coercive pressures operate across levels of governance will be critical for anticipating policy trajectories.

Second, although this chapter focuses on autonomous vehicle (AV) regulation, the findings may not generalize to all domains of emerging technology governance. AV policy is characterized by high uncertainty, rapid technological change, and elevated public visibility, features that may heighten convergence pressures and constrain strategic experimentation. Future research should examine whether similar dynamics, particularly the contrast between structural and direct competition, emerge in other regulatory arenas such as artificial intelligence, data privacy, or climate technology.

Third, while this study captures regulatory capacity through academic and political expertise, these proxies are necessarily partial. Other institutional features, such as bureaucratic professionalism, industry ties, or participation in policy networks, may also shape a state's ability to diverge from competitors. Future studies could benefit from qualitative or mixed-methods research that examines the mechanisms through which capacity enables innovation, particularly in politically contested or technically complex policy environments.

Chapter 3 Contextualizing the Framing Effects of Policy Adoption: Interstate Competition and Autonomous Vehicle Discourse in the U.S.

3.1 Introduction

When new technologies emerge, they often prompt diverse, even competing, interpretations of their definition, value, and societal implications (Felt 2015; Jasanoff 2005; Pinch and Bijker 1987). These technologies may be framed as engines of economic growth and innovation, but also as potential sources of ethical risk, inequality, or social harm. Such framing contests shape not only how technologies are publicly understood, but also how they should be regulated, adopted, and governed (Borah 2011; Nisbet 2014). In rapidly growing technological sectors such as artificial intelligence, biotechnology, and autonomous vehicles, the framing of these technologies can profoundly affect policy trajectories, public acceptance, and ultimate social outcomes (Felt 2015; Lempiälä et al. 2019; Stilgoe 2018; Ulnicane et al. 2021). Therefore, understanding why certain frames gain prominence while others are marginalized is crucial for both scholars and policymakers.

A substantial body of research in frame theory has examined how certain interpretations come to dominate public discourse. Key mechanisms include cultural resonance, elite cues, media gatekeeping, discursive opportunity structures, and advocacy networks (Benford and Snow 2000; Gamson and Modigliani 1989; Schön and Rein 1994). Among these, the discursive effect of policy adoption plays a particularly important role in shaping how emerging technologies are framed. Policy adoption serves as a visible and authoritative signal, indicating

that a government has taken a stance on a technology's social and political relevance (Edelman 1964; Schmidt 2008). Especially during the early stages of technological development, when meanings remain fluid and contested, adoption represents a turning point. It signals institutional recognition and invites interpretation by media, industry, academic, and the public (Birkland 1998; Felt 2015; Hilgartner and Bosk 1988).

Several policy theories help explain why policy adoption can exert a strong influence on public discourse. Policy feedback theory argues that policies not only reflect political preferences but also reshape interpretive contexts through "ideational feedback," elevating certain narratives, actors, and frames (Béland 2009; Mettler 2005; Pierson 1993). Agenda-setting and punctuated equilibrium theories suggest that adoption can serve as a focal event, concentrating media attention, stabilizing framing contests, and reinforcing dominant "policy images" (Baumgartner and Jones 1993; Green-Pedersen and Walgrave 2014; Jacobs and Weaver 2015). Discursive institutionalism further emphasizes how policies operate as tools of public justification, enabling elites to coordinate narratives and legitimize certain interpretations (Schmidt 2008).

Across these traditions, scholars emphasize that policy adoption is not merely a regulatory act but also a symbolic signal and discursive intervention, particularly in unsettled domains like emerging technology. However, most existing research on the discursive effects of policy adoption tends to treat jurisdictions as analytically isolated units. When contextual factors are considered, the focus is predominantly on internal determinants such as policy content, administrative design, partisan control, or state-specific institutional histories (Berry and Berry 1990; Campbell 2012; Mettler and Soss 2004). These accounts often assume that policy adoption produces relatively uniform effects on public framing when states exhibit similar internal characteristics.

In this paper, I argue that such analyses overlook a crucial dimension: the relational context in which policy adoption occurs. Jurisdictions are embedded in broader intergovernmental networks, observing and responding to one another's actions. Drawing on insights from the policy diffusion literature, I propose that the discursive effects of policy adoption should be understood as context-dependent, shaped by a state's position in a broader landscape of interjurisdictional relationship. Rather than viewing framing as a direct function of policy enactment alone, we must consider how external pressures condition the meaning and reception of adopted policies.

Among interjurisdictional dynamics, interstate competition is especially consequential for emerging technologies. In these domains, states increasingly vie for private investment, skilled labor, corporate partnerships, and reputational advantage (Gilardi and Wasserfallen 2019; Volden, et al. 2008). In such environments, policy adoption is often framed as a signal of technological leadership and innovation readiness (Schneider and Ingram 1993; Ulnicane et al. 2021). This paper treats competition as the key contextual factor shaping how media framing responds to policy change. I theorize that in high-competition states, policy adoption will amplify pro-innovation frames and suppress ethical or critical ones. In low-competition states, where reputational pressure is weaker, framing responses may be less coherent, more diffuse, or even oppositional. This variation suggests that the discursive effects of policy adoption are not uniform but contingent on the relational pressures states face.

To evaluate this framework, I focus on autonomous vehicle (AV) policy adoption and local media discourse across U.S. states. This case is especially well-suited for three reasons. First, AVs represent an ambiguous and evolving technology, giving rise to a wide range of competing frames, including economic opportunity, technological innovation, ethical risk, and

social concern (Hemesath and Tepe 2023; Stilgoe and Mladenović 2022). Second, AV policy adoption in the U.S. has been uneven and decentralized, with states enacting policies at different times and in different ways, making it a strong setting for testing the effects of policy adoption. Third, AV development has become a focal point of state-level competition, as states seek to position themselves as leaders in attracting investment, talent, and technological advancement (Anderson et al. 2016). These features make AV policy an ideal context for analyzing how framing evolves under conditions of interstate competition.

I constructed a dataset of AV-related media coverage from local newspapers across U.S. states between 2012 and 2022. I use a Sentence-BERT (SBERT) based semantic classification method to detect the presence of three key frame types: economic, technological/innovative, and social/ethical. SBERT allows for the identification of paragraph-level semantic similarity between media text and predefined conceptual frames, offering greater contextual sensitivity than word-embedding techniques or topic-modeling approaches. I then implement a staggered difference-in-differences (DiD) design to estimate the causal effect of AV policy adoption on frame prevalence, comparing trends across high- and low-competition states.

This research makes several contributions. First, it advances theories of policy's framing effects by showing that they are not uniform, but contingent on interjurisdictional relationships, specifically, the competitive pressures states face within a broader policy field. Second, it bridges policy diffusion and framing literatures by demonstrating that diffusion mechanisms do not merely influence whether and when policies are adopted but also shape how those policies are framed and interpreted in public discourse. Third, it introduces a novel computational classification method for identifying frames at scale, offering a transferable tool for analyzing media discourse across diverse policy domains.

3.2 Theoretical Framework

3.2.1 Policy Adoption as a Discursive Signal

Emerging technologies often become sites of contestation over their meaning, value, and role in society. Unlike established technologies, emerging technologies are shaped by competing narratives that link them to different economic, political, and ethical concerns. For instance, artificial intelligence is alternately framed as a driver of economic progress or a source of existential risk (Cave et al. 2019), biotechnology as either a medical breakthrough or an ethical minefield (Jasanoff 2005), nanotechnology as a revolutionary innovation or a field marked by uncertainty and public concern (Pidgeon et al. 2009), and autonomous vehicles as solutions to mobility challenges or threats to labor and safety (Stilgoe 2018). These framings are not merely descriptive; they actively shape how regulatory problems are constructed, which policy tools are considered legitimate, and how state interventions are justified. Understanding why certain frames gain traction while others are marginalized is, therefore, crucial.

Frame theories have identified a range of mechanisms through which certain interpretations of contested issues come to dominate public discourse. Some emphasize how frames are constructed and made resonant, highlighting cultural narratives and interpretive packages (Gamson and Modigliani 1989), strategic framing in advocacy networks (Snow and Benford 1988), and the alignment of policy stories with shared cultural understandings (Jones and McBeth 2010). Others focus on the institutional and political forces that amplify particular frames, such as sponsorship by powerful actors (Benford and Snow 2000), selective reinforcement by policy and media institutions (Ferree et al. 2002), and discursive opportunity structures (Koopmans and Statham 1999). Other research examines the role of media and communication, especially gatekeeping practices that shape which frames gain visibility and how

they are presented (Entman 1993). These dynamics are especially salient in the context of contested issues, where public meanings remain fluid and institutional narratives are still forming.

Among these mechanisms, policy adoption warrants particular attention, especially in the context of contested issues like emerging technologies. This is because policy acts as a visible, authoritative signal that a government has taken a position on the social and political significance of a technology. As Deborah Stone (1989) argues, policies are not just administrative tools but vehicles for causal stories that define problems and prescribe solutions. Once adopted, these narratives become embedded in official discourse, shaping how the issue is communicated to the public. In the early stages of technological emergence, when meanings remain fluid and contested, policy adoption often marks a turning point: it signals that a technology is no longer speculative but officially recognized and politically actionable. Unlike broader media or corporate discourse, policy adoption is a discrete, authoritative act that invites interpretation by journalists, firms, advocacy groups, and the public. Especially for technologies not yet integrated into daily life, such adoption can catalyze discursive shifts, amplifying certain narratives while sidelining others.

Several strands of policy theory help explain how and why policy adoption shapes public framing. Policy feedback theory, in particular, emphasizes that policies do not simply reflect existing preferences but actively shape them by altering the interpretive and institutional environment in which actors operate (Mettler 2005; Pierson 1993). Policies generate what Béland (2009) terms "ideational feedback," influencing how issues are understood by validating certain narratives, elevating specific interests, and defining the cognitive frames available for interpretation. These feedback effects can be positive, reinforcing dominant understandings and

encouraging alignment with the policy's goals, or negative, triggering resistance, reframing, or contestation by actors who perceive the policy as exclusionary or misaligned with their values. In the case of emerging technologies, policy adoption may not only generate administrative outcomes but also help define what the technology is, why it matters, and how it should be imagined by society.

Agenda-setting theories suggest that the enactment of a policy can focus public and media attention on an issue, thereby influencing how it is framed. As part of this tradition, Baumgartner and Jones's (1993) Punctuated Equilibrium Theory argues that public debates usually move slowly, but occasionally experience sudden shifts when a new way of thinking, what they call a "policy image", gains momentum. Policy adoption can trigger such a shift by sending a strong signal about how the issue should be understood. Similarly, Vivien Schmidt's discursive institutionalism highlights how policies function not just as tools of governance but as vehicles for public justification. According to Schmidt (2008), policy adoption lends credibility and legitimacy to certain interpretations of an issue, making them appear more authoritative or commonsensical. Importantly, the framing power of a policy does not necessarily depend on its technical content; rather, it stems from the institutional authority and symbolic weight that adoption confers. As a result, policy adoption can subtly redefine what kinds of narratives, concerns, or solutions are considered appropriate—particularly in domains like emerging technology, where meanings are fluid and under construction.

Numerous empirical research demonstrates that policy adoption, especially in areas involving emerging technologies or innovation-driven policy change, can shape public and media discourse. Gamson and Modigliani (1989) showed that shifts in U.S. nuclear energy policy corresponded with evolving media "interpretive packages," as official decisions helped

legitimize certain frames. Bareis and Katzenbach (2021) argue that national AI strategies function as performative interventions, framing AI as a national priority and shaping its social meaning. Schiff (2024) similarly finds that congressional adoption of AI-related proposals triggered increased alignment around competitiveness and innovation frames in media coverage. In the energy sector, policy events such as renewable mandates and cap-and-trade adoption have been shown to influence framing, often shifting media narratives toward economic modernization and energy independence (Basseches 2024). Together, these studies suggest that policy adoption is not a neutral act but a discursive event that shapes which frames take hold and whose interpretations gain legitimacy.

3.2.2 The Contingent Framing Effects of Policy Adoption: The Role of Inter-State Competition

While prior literature has effectively demonstrated that policy adoption can shape public discourse, they frequently treat jurisdictions as analytically isolated units, assuming that the framing effects of policy adoption unfold uniformly across contexts. What remains underexplored is how these effects may vary contingent on interjurisdictional relationships. Jurisdictions do not operate in a vacuum; instead, they are influenced by one another. Therefore, it is crucial to understand that the discursive effects of policy adoption must be contextualized within a broader intergovernmental landscape (Gilardi and Wasserfallen 2019; Gulrajani and Moloney 2012; Meseguer 2005).

The policy diffusion literature has long emphasized the role of interjurisdictional relationships in shaping policy processes. In federated systems like the United States, and in global policy arenas more broadly, jurisdictions routinely observe and respond to one another's actions (Berry and Berry 1990; Shipan and Volden 2008). Policy decisions are thus shaped not

only by internal considerations but also by how states position themselves in relation to their peers. Scholars have specifically identified several mechanisms through which jurisdictions influence each other's adoption decisions, including emulation, learning, competition, and coercion (Böhmelt et al. 2022; True, Jones, and Baumgartner 2007). While this body of work primarily focuses on the policy adoption process itself, I argue that interjurisdictional relationships can shape not only whether policies are adopted but also how they are interpreted by the public and media. Therefore, this paper applies the policy diffusion literature's concept of interjurisdictional dynamics to understand how policy's framing effects are dependent on these relationships (Gilardi 2010; Karch 2007).

In this paper, I focus specifically on interstate competition as the central relational dynamic shaping the discursive effects of policy adoption. Among the mechanisms identified in diffusion theory, competition is particularly well-suited to explaining framing dynamics in domains such as emerging technologies, economic development, and innovation policy. States frequently compete for mobile capital, high-skilled jobs, and reputational advantage, seeking to position themselves as national leaders in innovation. This competitive pressure, well documented in both political economy and diffusion literatures (Breznitz and Murphree 2011; Gormley 1986), influences not only when and how policies are adopted but also how they are communicated and interpreted. In such settings, policy adoption becomes more than an act of regulation or problem-solving; it becomes a symbolic gesture of positioning the state relative to others. This signaling function is especially important in the context of emerging technologies, where uncertainty and public ambiguity create space for institutional actors, policymakers, media outlets, and industry coalitions to construct and compete over the meaning of technological change. These dynamics are especially meaningful in the current industrial and technological

environment, marked by rapid innovation, geopolitical tensions, and escalating competition for technological leadership.

This leads to a core theoretical proposition: the framing effects of policy adoption are contingent on a jurisdiction's intensity of competitive pressure. The same policy, when enacted under different interjurisdictional conditions, may elicit distinct narrative responses. This perspective introduces a contingent model of framing, one that incorporates interstate relational dynamics as a key factor conditioning how policy decisions are interpreted and communicated to the public. It extends existing research on policy feedback, diffusion, and framing by foregrounding the role of inter-jurisdictional competition in shaping discursive outcomes. In doing so, it highlights an important yet underexamined mechanism through which the institutional politics of federalism influence the cultural construction of emerging technologies. The following sections develop this framework by presenting hypotheses that differentiate between high-competition and low-competition state environments.

High-competition states

In high-competition states, where jurisdictions are acutely aware of rival states' actions and outcomes, policy adoption often serves as a visible signal of strategic alignment with innovation-led economic development. Political elites, economic stakeholders, and media actors in these environments tend to frame policy enactment as a competitive achievement, a demonstration that the state is keeping pace with, or ideally outpacing, others in securing technological leadership, attracting investment, and signaling regulatory readiness. According to agenda-setting and symbolic politics theories, this heightened salience encourages discursive prominence around narratives that emphasize opportunity, progress, and growth (Baumgartner and Jones 1993; Edelman 1988). In such contexts, local media are especially likely to pick up

elite cues and reinforce frames that present the policy as a forward-looking investment in the state's technological and economic future (Soss, Fording, and Schram 2011). The policy is no longer just a governance tool; it becomes a strategic communication device. As a result, I expect pro-innovation frames, particularly economic development and technological progress narratives, to increase in prominence following policy adoption in highly competitive states.

Hypothesis 1: *In high-competition states, policy enactment will lead to an increase in pro-innovation frames (economic and technological frames) in local media coverage.*

While high-competition states emphasize opportunity, they are also more likely to suppress or marginalize frames that introduce doubt, complexity, or conflict into the dominant narrative. Social and ethical concern frames, such as those focused on surveillance, equity, labor impacts, or algorithmic bias, often call attention to the risks and societal trade-offs associated with emerging technologies. In a competitive environment, where the goal is to attract mobile capital and project technological leadership, such frames can be politically inconvenient or strategically counterproductive. Research in policy communication and media framing suggests that actors will seek to align public discourse with a coherent image of success, minimizing dissenting or critical perspectives (Entman 2004; Schneider and Ingram 1997). Local media, in turn, may downplay these frames due to elite cue-taking, narrative coherence pressures, or editorial preferences that prioritize optimism and consensus. As such, the framing space in high-competition states is likely to contract around pro-innovation narratives, leading to a decline in critical or ethically concerned frames after policy adoption.

Hypothesis 2: *In high-competition states, policy enactment will lead to a decrease in social/ethical frames in local media coverage.*

Low Competition States

In contrast, low-competition states do not face the same pressure to perform or position themselves aggressively in the national race for technological or economic leadership. While they may adopt policies in similar domains, the symbolic intensity and strategic stakes attached to these adoptions are lower. As a result, political elites may be less likely to invest in coordinated messaging, and the media may approach coverage in a more routine, reactive, or fragmented manner. From a framing perspective, this means that policy adoption may not catalyze a strong narrative shift. Economic and technological frames may still appear, especially in coverage that recycles national or industry talking points, but the local amplification of these frames is likely to be muted. Without the external stimulus of regional rivalry, there is less incentive for stakeholders to frame the policy as a major innovation milestone or economic breakthrough. Thus, I expect only modest or inconsistent increases in pro-innovation framing in low-competition states.

Hypothesis 3: *In low-competition states, policy enactment will lead to a modest increase or no significant change in pro-innovation frames (economic and technological frames) in local media coverage.*

Low-competition environments also present fewer incentives to suppress dissenting or critical interpretations. In the absence of strong competitive pressures, there is more room for discursive pluralism, and less coordination around a unified pro-innovation narrative. This openness creates conditions in which social and ethical concern frames may persist or even expand following policy adoption. For instance, local journalists, community leaders, or advocacy organizations may raise questions about equity, data governance, or technological harms without fear of undermining an economic positioning strategy. Theories of discursive institutionalism and media responsiveness (Borah 2011; Cook 2005; Hilgartner 2000; Schmidt

2008) suggest that when elite signaling is weak or ambiguous, media framing becomes more diverse and less tightly managed. In such cases, policy adoption may act less as a signal of progress and more as a moment of public scrutiny or ambivalence. Therefore, I anticipate that in low-competition states, ethical or social concern frames will remain stable or even gain prominence after a policy is adopted.

Hypothesis 4: *In low-competition states, policy enactment will lead to no significant change or a possible increase in social/ethical frames in local media coverage.*

3.3 Research Setting

To test the hypotheses regarding the contingent effects of policy adoption on the framing of emerging technologies, this study examines autonomous vehicle (AV) policy enactments across U.S. states between 2012 and 2022. The diffusion of AV policy began in Nevada in 2011, making it the first state to authorize the testing of autonomous vehicles on public roads (Anderson et al. 2016). Since then, adoption has proceeded unevenly across states. AVs remain in the early stages of technological development, characterized by substantial uncertainty regarding their regulatory, social, and economic implications (Glancy 2015; Stilgoe 2018). There are no settled definitions of what AVs are, what problems they address, and what risks they introduce. This case provides an ideal empirical setting to evaluate the theoretical framework due to both conceptual and methodological advantages.

First, the discourse surrounding AVs is shaped by diverse and often competing frames, making it a strong example for analyzing how policy adoption influences public interpretation. Proponents commonly present AVs as engines of economic growth, emphasizing their potential to attract investment, create high-skill jobs, and establish states as hubs for R&D and mobility leadership (Hemesath and Tepe 2023). The innovative frame complements this view by

portraying AVs as solutions to long-standing issues like traffic fatalities, congestion, and labor shortages in logistics (Anderson et al. 2016). Together, these narratives form the pro-innovation frame that anchors one of this study's core hypotheses. In contrast, critical and ethical frames raise concerns about safety, privacy, algorithmic fairness, and social inequality. These include cybersecurity threats, surveillance risks from constant data collection, and fears that AV technologies may deepen existing exclusions rather than broaden access (Cohen and Cavoli 2019; Stilgoe and Mladenović 2022). These competing narratives provide a strong foundation for observing how media frames evolve in response to policy enactment.

Second, because AV policymaking in the U.S. is decentralized, it creates clear opportunities to study the treatment effects of policy adoption on public discourse. Without comprehensive federal regulation, states have developed their own AV laws, resulting in a patchwork of policies. While national events, such as high-profile AV crashes, can shape the broader media landscape, the passage of state-level legislation sends a clear and specific signal about how a state views the technology (Glancy 2015; Stilgoe 2021). For local media, these laws represent a formal shift in how the state positions itself, both symbolically and substantively. This structure makes AV policy adoption well-suited for a difference-in-differences (DiD) design, allowing for causal inference analysis.

Third, since AVs are still in a formative stage, it amplifies the interpretive power of policy adoption. Given the lack of consensus on what AVs are or how they should be governed, policy enactments have a substantial potential to shape dominant understandings of the technology. State-level legislation, therefore, does more than establish legal guidelines; it helps define what kind of technology AVs are understood to be. In many instances, policy adoption precedes widespread deployment, making it a primary avenue through which meaning is socially

constructed (Hilgartner and Bosk 1988; Jasanoff 2005). For this reason, AV policy is not merely a legal intervention but also a potent discursive act.

Finally, AV policymaking provides a compelling case for studying interstate competition. As states across the U.S. navigate broader transformations in economic structure and technological innovation, particularly those linked to artificial intelligence, autonomous vehicles have become a salient and visible domain of policy action. AVs exemplify how emerging technologies are not only advanced by firms but also actively shaped through regionally driven strategies and state-level interventions. In this landscape, the state functions as a key site for enabling, regulating, and attracting technological development. Crucially, the degree of competition varies across states depending on their industrial base, policy orientation, and strategic priorities. While some states aggressively pursue AV leadership as part of economic development efforts, others proceed more cautiously. This variation offers a valuable opportunity to test whether and how the discursive effects of policy adoption are shaped by a state's relative competitive positioning.

3.4 Methodology

3.4.1 Data and Sample

The unit of analysis in this study is the state-year. All key variables, including media framing and policy adoption, are measured or aggregated at this level. To capture the evolution of framing over time, I compiled a longitudinal dataset of news coverage on autonomous vehicles (AV) from representative local newspapers across 48 U.S. states[4]. The dataset spans the years 2012 through 2022, capturing the evolution of AV discourse, after Nevada's policy

[4] Alaska and Hawaii were excluded because their geographic isolation and policy context make them unsuitable for analyzing interstate competition dynamics.

adoption in 2011. Articles were collected from major news archive databases, including ProQuest, NewsBank (Access World News), and LexiNexis, which together provide comprehensive access to local news content from a wide range of U.S. states media outlets (see Appendix Table A.2 for a full list). Using keyword-based queries[5], I retrieved 13,171 articles related to AVs. This approach yielded a broad and representative sample of state-level media coverage, suitable for examining how public framing responds to policy adoption.

Frame classification was conducted at the paragraph level, rather than the article or sentence level. Full articles often contain multiple themes or unrelated content, and individual sentences frequently lack sufficient context for frame detection (Eisele et al. 2023; Grün and Hornik 2011). Paragraphs offer a more coherent and focused unit, typically expressing interpretable framing logics, such as AVs as economic opportunities, technological innovations, or ethical concerns, making them better suited for large-scale semantic classification.
From the initial 13,171 articles, 49,548 paragraphs were identified. However, many articles included paragraphs that discussed unrelated topics without directly engaging with AV issues. Including such paragraphs would introduce noise and compromise the accuracy of frame classification. To ensure analytic precision, I implemented a filtering process to retain only substantively relevant paragraphs. Using Sentence-BERT (SBERT), I calculated the semantic similarity between each paragraph and a reference definition of AVs[6]. Only paragraphs exceeding a predefined similarity threshold were retained.

[5] Keyword-based queries included terms such as “autonomous vehicle,” “self-driving car,” “driverless car,” “robot car,” and “connected vehicle.”

[6] The reference text for defining AV is "This paragraph is about autonomous vehicles, driverless cars, or self-driving technology. It may discuss related companies, industries, impacts, or policies, including economic factors such as job creation, investment, or market competitiveness; technological features such as innovation, automation, or safety systems or social and ethical issues such as fairness, privacy, labor displacement, or public trust."

The filtering process excluded approximately 65% of paragraphs, resulting in a final analytic sample of 49,548 AV-relevant paragraphs. It is from these filtered paragraphs that the proportion of each frame type is calculated for each state-year. Details on the filtering process and representative paragraph samples are provided in Appendix Table A.1, with a full summary of articles, paragraphs, and filtered AV content by state available in Appendix Table A.2.

To analyze the effect of policy on media framing, I also constructed a dataset of state-level AV policy enactments using the National Conference of State Legislatures (NCSL) Autonomous Vehicle Legislation Tracker. This source provides comprehensive, year-by-year documentation of AV policy activity across states. I supplemented this policy data with a set of state-level control variables, including employment rates, industrial composition, and population size, sourced from the U.S. Bureau of Labor Statistics and the U.S. Census Bureau.

3.4.2 Measures

Dependent Variable

The key dependent variables in this study are media frame proportions, which measure the relative emphasis on different types of frames in state-level newspaper coverage of autonomous vehicles (AVs) by year. To classify frames at the paragraph level across a large corpus, I used Sentence-BERT (SBERT), a transformer-based language model that produces dense, context-sensitive embeddings of short texts (Reimers and Gurevych 2019). I chose SBERT over alternatives such as Latent Dirichlet Allocation (LDA), Structural Topic Models (STM), and static word embeddings (e.g., Word2Vec, GloVe) because of its superior performance in capturing semantic nuance in short, variable-length texts like news paragraphs.

Topic models such as LDA and STM rely on word co-occurrence and typically perform best on long documents; applied to shorter texts, they often yield vague or incoherent topics that

poorly map onto theoretically defined frames. Similarly, traditional word embeddings produce static representations that cannot distinguish between meanings that vary by context. SBERT, by contrast, embeds full paragraphs using transformer-based architecture, enabling precise semantic comparisons between text segments and predefined reference frames (Walter and Ophir 2019). This makes it especially effective for identifying frame categories in large-scale media discourse (Ma et al. 2023).

Using the filtered AV-relevant paragraphs, I classified each into one of three target frame categories: economic, technological/innovative, and social/ethical. Each frame was operationalized using a reference text crafted to reflect its core conceptual meaning. The three frames were defined as follows:

Economic Frame: "This paragraph discusses the economic impacts of autonomous vehicles, including how AVs may contribute to business growth, job creation, talent attraction, or regional competitiveness. It may describe public-private partnerships, new ventures, cost-efficiency, or how AVs can boost individual productivity. It may also mention how cities or states compete to attract AV firms or position themselves as technology hubs."

Technological/Innovation Frame: "This paragraph discusses the technological features or innovative potential of autonomous vehicles, such as the use of artificial intelligence, sensors, detection systems, or automation. It may describe engineering breakthroughs, prototypes, testing programs, or technical readiness levels. It may also highlight how AVs can reduce traffic accidents, lower emissions, improve mobility for people with disabilities, or solve social problems through innovation. The tone may reflect optimism, techno-solutionism, or belief in the transformative power of technology."

Social/Ethical Frame: "This paragraph discusses the social or ethical concerns associated with autonomous vehicles, such as labor displacement, safety risks, privacy violations, data collection, hacking, or bias in decision-making. It may describe moral dilemmas like the trolley problem, public fear or distrust, or uncertainty about legal responsibility and liability in the event of an accident. It may also highlight inequality in access, surveillance risks, or lack of regulatory oversight, raising broader questions about the social consequences of AVs."

The economic frame emphasizes AVs as engines of growth, investment, job creation, and regional competitiveness. The technological frame focuses on innovations such as artificial intelligence, sensors, and automation, often casting AVs as solutions to pressing societal problems. The social/ethical frame foregrounds concerns related to liability, privacy, labor displacement, safety dilemmas, and regulatory uncertainty.

To classify frames, I compared each paragraph to the three predefined frame reference text using Sentence-BERT. The model calculated how similar each paragraph was to each frame by measuring the cosine similarity between their semantic embeddings. A paragraph was assigned to the frame it most closely matched, as long as the similarity score was above a certain threshold. If no frame matched strongly enough, the paragraph was labeled as "unframed" to avoid forcing a classification where none fit. Supplementary Appendix A.3 provides real examples from the dataset to illustrate how this process captures actual framing patterns in the media.

To construct the state-level dependent variables, I aggregated the classified paragraphs to the state-year level. For each U.S. state s and year t, I calculated the proportion of AV-relevant paragraphs assigned to each frame using the following formula:

$$Frame\ Proprotion_{s,t} = \left(\frac{Number\ of\ Paragraphs\ Classified\ to\ a\ given\ Frame}{Total\ AV-relevant\ Paragraphs\ in\ state\ s\ and\ year\ t}\right)$$

This process produced three continuous dependent variables: the proportions of economic frames, technological/innovation frames, and social/ethical frames in each state-year. These serve as the key outcomes in the subsequent analysis, capturing how different dimensions of AV discourse evolve in response to policy adoption. Because some paragraphs were categorized as 'unframed,' the proportions of the three frame categories do not necessarily sum to one within each state-year. Full methodological details, including similarity thresholds, embedding techniques, and robustness checks, are available in the Supplementary Appendix.

Independent Variables

Treatment: Policy Adoption

The key independent variable is a binary treatment indicator that captures the adoption of autonomous vehicle (AV) policy at the state level. For each U.S. state, the indicator switches from 0 to 1 in the year the state first enacts an AV-related law or executive order, and remains 1 thereafter. This variable represents the treatment in the staggered difference-in-differences (DiD) design and is used to estimate the causal effect of policy adoption on state-level media framing outcomes.

Moderating Variable: Inter-State Competition (High vs. Low)

To assess whether the effect of AV policy adoption on media framing varies by inter-state competition, I include a moderating variable that captures a state's relative competitive pressure. I use a network-based measure of competition derived from patterns of workforce mobility between states in relevant industries. Specifically, if a significant share of workers moves from state i to state j, then i is likely to view j as a competitor. When j adopts an AV-related policy, i may perceive pressure to respond similarly.

This direct competition effect is formalized as:

$$Direct\ Competition\ Effect_{it} = \sum_{j} \left(AV\ Bills_{jt-1}\right)\ X\ \left(\frac{Worker\ Move_{ijt-1}}{Worker\ Move_{it-1)}}\right)^2$$

This formulation weights the influence of other states by both their policy activity and the strength of their workforce connections to the focal state. The squared term gives greater weight to stronger ties, under the assumption that they exert a more substantial influence.

Based on this measure, I classify each state-year into one of two groups: high competition or low competition. This classification is used to stratify the analysis and estimate treatment effects separately for high- and low-competition states. For states that never adopted AV policies during the study period, I assign competition status based on their final year of observed competitive pressure.

3.4.3 Analytical Approach

This study employs a staggered difference-in-differences (DiD) method developed by Callaway and Sant'Anna (2021) to estimate the causal effect of state-level AV policy adoption on media framing, and to assess how this effect varies across different competitive contexts. The staggered DiD framework is particularly well-suited for cases where units adopt treatment at different points in time. Because U.S. states adopted autonomous vehicle policies at varying times between 2012 and 2022, I required a statistical approach that explicitly accounts for this staggered treatment structure. The Callaway and Sant'Anna method is designed for exactly this context, allowing for valid comparisons and reliable estimation under heterogeneous treatment timing.

I selected this estimator over conventional DiD models (typically implemented via two-way fixed effects) because such models can yield biased estimates in staggered adoption settings, especially when treatment effects are heterogeneous across states or evolve over time (Goodman-

Bacon 2021). Conventional DiD estimators often compare early adopters to later adopters, which can lead to inappropriate comparisons and violate the parallel trends assumption. By contrast, the Callaway and Sant'Anna method constructs comparisons between treated states and a valid control group composed of states that are untreated or not-yet-treated at each time point. It then estimates group-time average treatment effects (ATTs), which are aggregated to produce overall effects. This structure improves both the transparency and validity of causal inference in staggered treatment settings (Rios-Avila 2022).

A further advantage of this estimator is that it allows estimation of dynamic treatment effects, capturing how outcomes evolve over time relative to the moment of policy adoption. These event-time estimates provide insight into whether changes in media framing occur immediately, are delayed, or persist over time. They also enable visual and statistical testing of the parallel trends assumption by comparing pre-treatment trajectories between treated and control states.

The analytic setup is as follows. The dependent variables are the state-year proportions of paragraphs classified as economic, technological, or social/ethical frames, as described in the previous section. The treatment variable is a binary indicator coded as 1 in the first year a state adopts an AV policy and in all subsequent years. This structure enables identification of the causal impact of policy adoption on changes in media framing, relative to states that had not yet adopted a policy at that time. In addition, to test whether this effect is conditioned by inter-state competition, I divide the sample into high-competition and low-competition states groups. Rather than using interaction terms, I estimate the treatment effect separately for each group. This subsample approach allows for a clear test of the hypothesis that framing responses to policy adoption vary depending on a state's competitive position.

3.5 Results

3.5.1 Descriptives

Timing of AV policy adoptions

Figure 3.1 presents a histogram of the first-year AV policy enactments across U.S. states from 2012 to 2022. During this period, a total of 44 states adopted autonomous vehicle legislation or executive policies for the first time, while 6 states remained untreated through the end of the observation window. As the figure illustrates, AV policy adoption did not unfold evenly across time. Instead, adoption was heavily clustered in a short span between 2017 and 2019, during which over two-thirds of the treated states passed their first AV-related law. This wave of legislative activity reflects a critical inflection point in the diffusion of AV governance across state governments, possibly driven by increased technological readiness, intensified industry lobbying, and growing inter-state competitive pressure to attract investment and innovation.

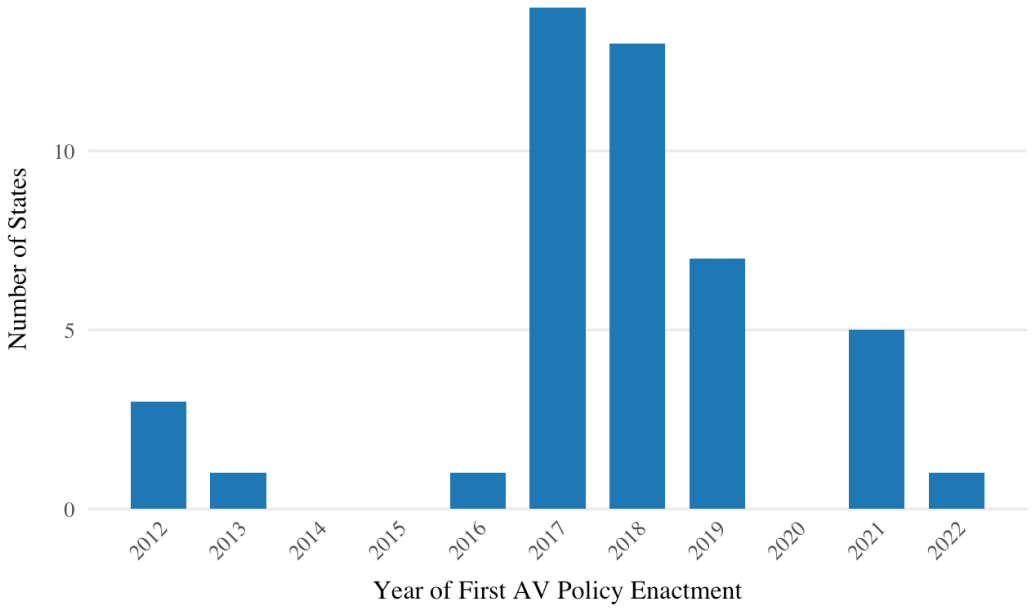


Figure 3.1 Distribution of First-Year AV Policy Enactments across U.S. States (2012–2022)

Temporal Trends in AV Framing

Figure 3.2 displays the evolution of media framing around autonomous vehicles over the 2012–2022 period, focusing on three analytically distinct frames: economic, technological/innovative, and social/ethical. These proportions reflect the share of each frame type among all identified paragraphs referencing AVs in the local media corpus. The sum of all frame proportions within each year does not equal 1 because some paragraphs are categorized as "unframed." Overall, the most consistently dominant frame throughout the period is the technological frame, which fluctuates within a relatively narrow band and underscores the enduring role of innovation and futurism in AV discourse. This stable prominence reflects how AVs have been discursively anchored in narratives of technological progress, engineering breakthroughs, and innovative aspects.

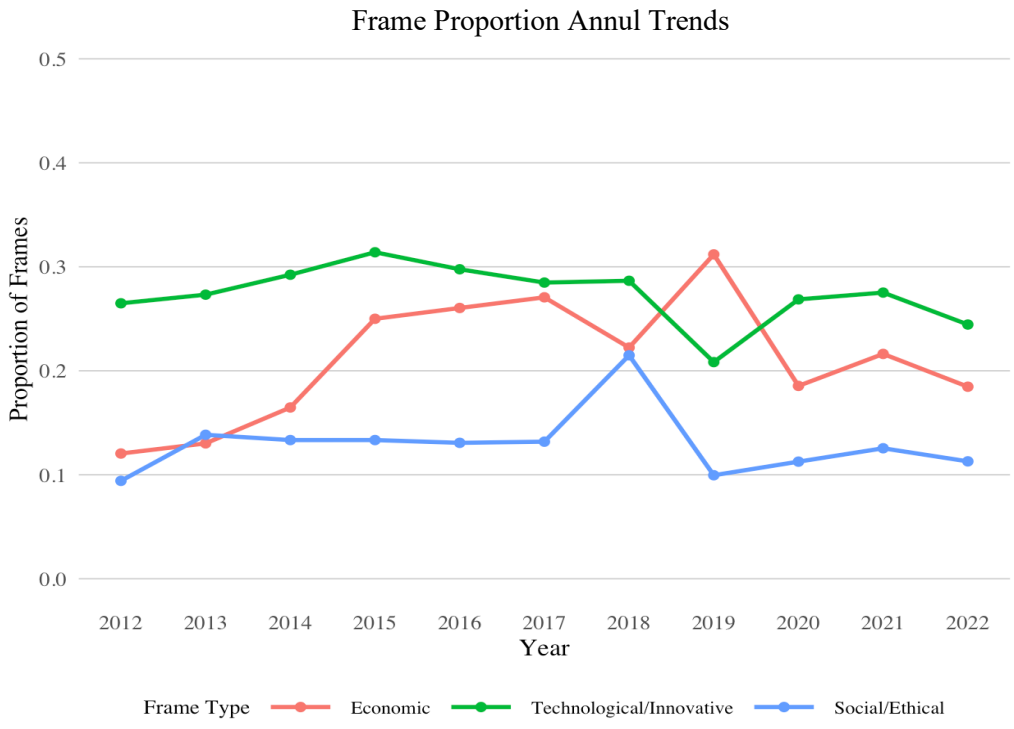


Figure 3.2 Annual Trends in Autonomous Vehicle Frame Proportions across U.S. States (2012–2022)

Economic frames, by contrast, exhibit a more dynamic pattern. Beginning at just over 10% in 2012, economic framing grew steadily through the mid-2010s, peaking around 2019, briefly surpassing technological frames in relative salience. This rise may reflect increasing emphasis on AVs as engines of economic growth, job creation, and regional competitiveness, particularly as state governments sought to attract AV testing and deployment (Béland and Cox 2016). After 2019, however, economic framing declined, potentially due to the plateauing of AV investment and heightened public skepticism about commercial viability.

The social/ethical frame is consistently the least prominent across the dataset, especially when compared to the economic and technological frames. This likely reflects the broader tendency of public and media discourse on autonomous vehicles to emphasize innovation and economic potential, while giving less attention to concerns such as equity, safety, or social risk. A notable exception occurs in 2018, when the proportion of social/ethical framing spikes to over 21 percent. This surge likely corresponds to the fatal crash involving an Uber self-driving car in Tempe, Arizona, which generated intense media scrutiny and public debate around issues of safety, liability, and algorithmic accountability.

3.5.2 Statistical Results

Average Treatment Effects from Staggered Difference-in-Differences

Table 3.1 presents average treatment effects (ATT) of AV policy adoption on the proportion of three dominant frames, economic, technological/innovative, and social/ethical, using a staggered difference-in-differences approach. Estimates are reported for all states, as well as separately for high- and low-competition states based on regulatory competition at the time of policy enactment.

Table 3.1 Average Treatment Effects of AV Policy Adoption on Frame Proportions, by Competition Context (Staggered Difference-in-Differences Estimates)

Dependent Variables (Frame Proportion)	All States	High-Competition States	Low-Competition States
Economic Frame	-0.037	0.091***	0.008
	(0.049)	(0.025)	(0.051)
Tech/Innov Frame	-0.009	0.022	-0.022
	(0.041)	(0.041)	(0.093)
Soc/Ethical Frame	-0.088	-0.161**	-0.039
	(0.049)	(0.064)	(0.045)
Obs. (state-years)	539	242	297

Note: Table reports average treatment effects on the treated (ATT) from staggered difference-in-differences models. The dependent variable is the proportion of each frame type within a state-year (economic, technological/innovative, and social/ethical). Models are estimated separately for all states, high-competition states, and low-competition states. Standard errors are in parentheses.
*$p < .05$, **$p < .01$, ***$p < .001$ (two-tailed tests.).

While no statistically significant effects are detected in the full sample, the disaggregated models reveal strong and significant framing shifts in high-competition states. In these states, AV policy adoption leads to a 9.1 percentage point increase in the use of economic frames ($p < 0.001$), and a 16.1 percentage point decrease in social/ethical frames ($p < 0.01$). These shifts are substantively large, reflecting considerable changes in the dominant narratives surrounding AVs in the years following policy enactment. No significant change is observed for technological/innovative frames. Like the full sample, no significant effects are found in low-competition states across any of the frame categories.

These findings offer empirical support for both Hypothesis 1 (policy adoption in high-competition states leads to an increase in pro-innovation frames) and Hypothesis 2 (policy adoption leads to a corresponding decrease in critical or ethical frames). The divergence across competition contexts suggests that the framing effects of policy adoption are contingent on inter-state dynamics. In high-competition states, policy functions not only as a governance mechanism

but also as a discursive signal, aligning media narratives with economic ambitions. Notably, the sharp decline in social and ethical framing underscores how critical concerns may be actively de-emphasized in competitive policy environments.

No statistically significant effects of technological frames are also noteworthy. One possible explanation is that technological discourse constitutes a stable background narrative in AV coverage, frequently invoked, but not particularly sensitive to policy timing or political context. Its consistency may reflect a broader cultural assumption about AVs as inherently technological artifacts, thus limiting the space for observable change (Stilgoe 2020).
The null findings in low-competition states provide little support for Hypotheses 3 and 4. As predicted in Hypothesis 3, policy adoption in these contexts does not produce a significant increase in pro-innovation frames; both economic and technological narratives remain statistically unchanged following enactment. Likewise, consistent with Hypothesis 4, no meaningful shift is detected in social or ethical framing. These results suggest that in the absence of strong competitive pressure, AV policy adoption lacks the symbolic force necessary to reconfigure media narratives. Rather than catalyzing discursive change, policy enactment in low-competition environments appears to be absorbed into pre-existing framing dynamics, reinforcing the argument that regulatory competition is a critical moderator of policy's interpretive effects.

In sum, these results demonstrate that policy adoption exerts a selective discursive effect, reinforcing economically optimistic narratives while marginalizing ethical concerns, but only in the presence of inter-state competition. This finding reinforces the theoretical claim that regulatory competition conditions not only policy formation, but also the symbolic and narrative consequences of policy adoption itself.

Dynamic Treatment Effects: Event Study Results

One of the strengths of the staggered difference-in-differences design is its capacity to estimate dynamic treatment effects over time. Rather than summarizing post-treatment effects with a single average, the event study specification traces out how frame proportions evolve in the years immediately preceding and following policy adoption. This approach not only reveals the temporal structure of treatment effects but also enables visual inspection of the parallel trends assumption, which is central to the validity of DiD designs.

Figure 3.3 presents the dynamic effects separately for high- and low-competition states across three framing outcomes: economic, technological/innovative, and social/ethical. These are supplemented by the full coefficient estimates and standard errors in Table 3.2.

Economic Frames

The results for economic frames show temporally structured policy-induced increases in high-competition states. A significant treatment effect emerges immediately in the year of policy adoption ($t = 0$, $\beta = 0.181$, $p < 0.01$), indicating that policy enactment serves as a strong discursive signal. This immediate uptick suggests that economic narratives that emphasize economic growth are mobilized quickly in response to policy change, likely by public officials, industry advocates, and media outlets seeking to frame the legislation as economically advantageous. In addition, the second statistically significant increase appears at three years post-enactment ($t = 3$, $\beta = 0.189$, $p < 0.01$), suggesting a sustained discourse toward economic justifications. This enduring presence indicates that the policy continues to anchor pro-innovation economic narratives beyond the moment of adoption, potentially due to ongoing implementation processes, follow-on investments, or recurring references to the legislation in political messaging.

Table 3.2 Event Study Estimates of the Dynamic Effects of Policy Adoption on Frame Proportions, by Competition Context (Staggered Difference-in-Differences Estimates)

	High Competition States			Low Competition States		
Event	Economic Frames	Tech/Innov Frames	Ethical Frames	Economic Frames	Tech/Innov Frames	Ethical Frames
-3	0.036	-0.086	0.098*	0.089	-0.045	-0.021
	(0.034)	(0.090)	(0.039)	(0.071)	(0.078)	(0.068)
-2	-0.003	0.086	-0.044	0.009	0.094	0.108*
	(0.055)	(0.094)	(0.033)	(0.049)	(0.056)	(0.047)
-1	-0.059	-0.039	0.025	0.022	0.030	-0.062
	(0.055)	(0.084)	(0.036)	(0.063)	(0.076)	(0.033)
0	0.181**	-0.001	-0.116	0.032	0.024	-0.044
	(0.056)	(0.079)	(0.089)	(0.038)	(0.085)	(0.054)
1	0.0158	0.088	-0.236*	0.030	0.013	-0.049
	(0.049)	(0.071)	(0.116)	(0.048)	(0.174)	(0.096)
2	-0.049	0.205*	-0.269***	0.088	-0.199**	-0.035
	(0.068)	(0.103)	(0.071)	(0.099)	(0.065)	(0.039)
3	0.189**	0.024	-0.179**	-0.292*	0.010	0.130
	(0.069)	(0.088)	(0.064)	(0.129)	(0.149)	(0.097)

Note: Table reports event study coefficients (ATT) for each frame by competition level. Effects are estimated for each year relative to the year immediately prior to policy adoption (t=-1). Standard errors are in parentheses.
*$p < .05$, **$p < .01$, ***$p < .001$ (two-tailed tests.).

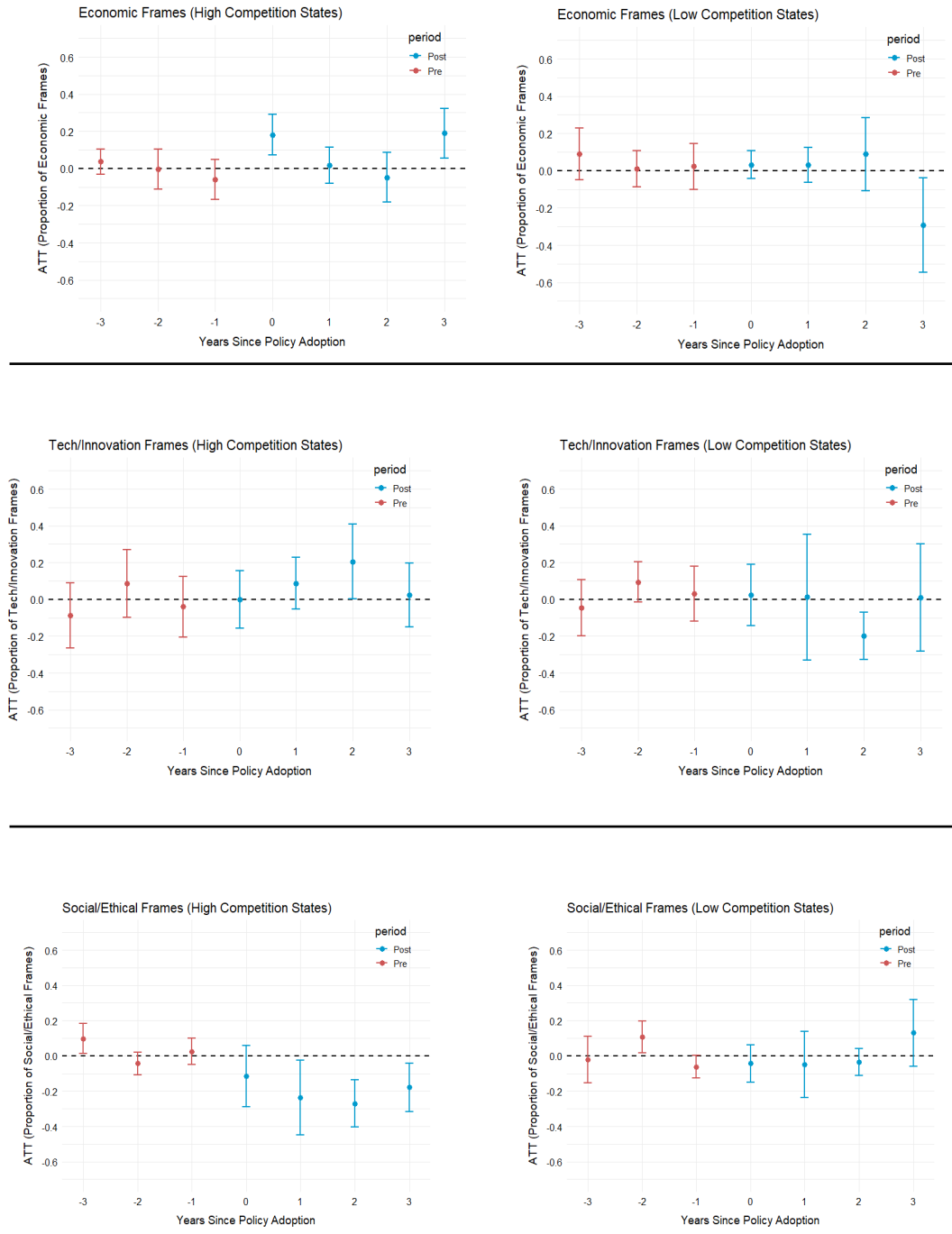


Figure 3.3 Dynamic treatment effects (event study estimates)

Together, these dynamic estimates reinforce the ATT results but also reveal that the impact of policy adoption on economic framing is both rapid and persistent, shaping the symbolic environment over a multi-year period. This pattern aligns with Hypothesis 1, which posits that AV policy in competitive contexts catalyzes economic framing by incentivizing states to position themselves as pro-growth, innovation-forward jurisdictions in a national regulatory landscape increasingly shaped by inter-state competition.

In contrast, low-competition states show no significant changes in economic frames until three years post-treatment ($t = 3$), where a negative and marginally significant coefficient emerges ($\beta = –0.292$, $p < 0.05$). This late decline is difficult to interpret definitively, but may reflect delayed disillusionment or alternative framing pressures in environments less shaped by competitive incentive structures. It is surprising, however, that policy adoption appears to have no immediate or positive effect on economic discourse in low-competition contexts. Given the common association between AV legislation and economic opportunity, the absence of an increase in pro-growth framing suggests that without competitive pressure, policy adoption may lack the discursive force to reorient public narratives toward economic development.

Technological/Innovative Frames

The technological/innovative frame results show no consistent or significant effects in either competitive context. In high-competition states, none of the post-treatment coefficients reach statistical significance. A single positive coefficient appears at $t = 2$ ($\beta = 0.205$, $p < 0.05$), but its transience and lack of supporting patterns across other years suggest caution in interpretation. In low-competition states, the only significant coefficient is negative at $t = 2$ ($\beta = –0.199$, $p < 0.01$), but again without sustained or coherent trend structure.

Although technological/innovation frames show a modest upward trend following policy adoption in high-competition states, these changes are not statistically significant. This suggests that while the discourse may tilt slightly toward innovation rhetoric, technological frames are not strongly shaped by policy signals in the way economic frames are. One possible explanation is that technological narratives are already pervasive in AV discourse and thus function as a stable background frame, but less sensitive to changes in political or regulatory context. As such, the results partially support Hypothesis 1, but also indicate that not all pro-innovation narratives respond equally to policy enactment. This highlights the importance of distinguishing between economic and technological dimensions of innovation discourse in policy feedback analysis.

Social/Ethical Frames

The clearest and most persistent dynamic pattern emerges for social/ethical frames, particularly in high-competition states. As shown in Figure 3 and detailed in Table 2, the proportion of social and ethical discourse declines significantly in each of the three years following policy adoption: in the first year ($t = 1$), the treatment effect is -0.236 ($p < 0.05$); in the second year ($t = 2$), the effect intensifies to -0.269 ($p < 0.001$); and in the third year ($t = 3$), the decline remains sizable and significant at -0.179 ($p < 0.01$). This pattern not only confirms the average treatment effect reported earlier, but also reveals that the discursive suppression of ethical concerns is not a one-off event but it accumulates over time.

The timing and trajectory of this shift suggest that policy adoption in competitive states produces a structural reordering of the discursive field, in which critical perspectives, such as concerns over safety, equity, labor, or surveillance, become increasingly marginalized. Rather than triggering a short-lived framing response, policy adoption appears to catalyze a deeper realignment in which pro-innovation narratives crowd out or delegitimize social and ethical

critique. These results reinforce the idea that AV policies function not only as legal instruments but also as symbolic interventions disincentivizing oppositional or reflective voices.

By contrast, in low-competition states, no significant treatment effects are observed for social/ethical frames at any point in the post-adoption period. This absence of change reinforces the conditional nature of policy feedback: where regulatory competition is weak, the symbolic force of policy adoption appears insufficient to reshape the discursive environment. In these states, ethical discourse remains relatively stable, suggesting that the presence of policy alone is not enough to suppress critical framing, rather, such suppression requires alignment with competitive pressures that reward promotional framing and marginalize dissent.

The results offer strong support for Hypothesis 2, which posited that policy adoption would lead to a decline in critical or ethical frames in high-competition states. Moreover, the event study structure makes clear that this suppression is not only statistically robust but temporally coherent, with effects that emerge one year after adoption and persist thereafter. These findings highlight how state-level policy adoption, when embedded within a competitive field, can contribute to the erosion of deliberative pluralism in emerging technology governance. These results also speak to Hypothesis 4, which proposed that in low-competition states, policy adoption might lead to a modest increase or at least stability in ethical or social concern frames. While the findings confirm that ethical framing did not significantly decline, there is little evidence of a positive effect either. In other words, the expectation that policy adoption might activate or elevate ethical discourse in the absence of competitive pressure was not supported. Instead, ethical frames remained largely flat, suggesting that while low-competition environments do not suppress critical perspectives, they also do not necessarily amplify them.

This nuance reinforces the idea that symbolic effects of policy are not automatic but depend on the surrounding political incentives and discursive infrastructure.

Parallel Trends

The event study framework accompanied by figure 2 enables a direct and visual assessment of the parallel trends assumption, a core requirement for causal identification in difference-in-differences models. This assumption holds that, in the absence of treatment, the outcome trajectories of treated and control groups would have followed similar paths. In this case, the pre-treatment coefficients ($t = -3$ to $t = -1$) are statistically indistinguishable from zero across all three frames and both competition contexts, suggesting that treated and control states exhibited no differential trends prior to policy adoption. The absence of any anticipatory effects further rules out the possibility that changes in framing were already underway before treatment began.

This pattern provides strong empirical support for the identifying assumption, enhancing confidence in the claim that the observed post-treatment changes are indeed attributable to policy adoption, rather than to underlying differences in trend. It also mitigates concerns about reverse causality, such as the idea that shifts in framing might have driven policy adoption, since no framing divergence is detected in the years leading up to enactment.

3.6 Discussion

This study examined how state-level policy adoption influences the framing of autonomous vehicles (AVs) in local media, and how this effect is shaped by interstate competition. The empirical results reveal that the framing consequences of policy enactment are not uniform across jurisdictions. In states under highly competitive pressure, AV policy adoption was followed by an increase in economic framing and a significant decline in social or ethical

frames. By contrast, low-competition states exhibit only modest, statistically insignificant changes. Notably, technological frames remained relatively stable across contexts. These patterns suggest that policy adoption functions as a discursive signal, especially under competitive pressure, shaping how emerging technologies are interpreted in public discourse.

These results support the view that policy adoption is not merely a tool of governance but a symbolic act that reconfigures the meaning of emerging technologies. Consistent with theories of symbolic politics (Edelman 1988) and interpretive policy feedback (Béland 2009; Schneider and Ingram 1997), policy can serve as a communicative intervention that signals priorities, legitimizes specific futures, structures the terms of public debate, and implicitly sidelines alternative visions. In the case of AV policy, adoption appears to function as a framing cue for local media; once enacted, it becomes a rhetorical resource for journalists and state actors.

The core finding of this study is that the discursive impact of policy adoption is contingent on the competitive pressure a jurisdiction faces. In high-competition environments, where state governments operate under strong pressure to attract capital, talent, and prestige, policy adoption functions as a high-stakes symbolic act. It is part of a broader effort to signal innovation-readiness and regulatory leadership. Under these conditions, local media tend to amplify the economic dimensions of policy, aligning coverage with the promotional goals of political and industry elites. This pattern is consistent with theories of elite cue-taking and agenda-setting (Baumgartner and Jones 1993; Entman 2004), which suggest that under reputational pressure, political communication becomes more strategically curated. As a result, discursive diversity is reduced and frames that enhance state competitiveness are prioritized.

Highly competitive environment not only amplifies economic narratives but also systematically marginalizes ethical and social concerns. The pronounced decline in these frames

within high-competition states likely results from both strategic intent and structural dynamics. Public officials may deliberately avoid raising issues such as safety, labor displacement, or data privacy in order to maintain a forward-looking narrative centered on innovation and economic promise. At the same time, media outlets operating in these competitive contexts may selectively echo elite messaging, filtering out frames that complicate or contradict the dominant growth-oriented storyline. In such environments, critical perspectives are not merely absent, but are deprioritized within dominant political narratives. Concerns about equity, governance, and public accountability are often perceived as potential reputational liabilities, and as such, are deprioritized in favor of more promotional and investor-friendly discourse.

By contrast, in low-competition states, the amplifying effects on economic frames and the marginalization of ethical frames were not observed. This is likely because reputational stakes are lower, and the symbolic function of policy adoption is less pronounced in these contexts. As a result, the framing effects of policy tend to be weaker and more pluralistic. While economic and technological frames may still appear, they do not dominate public discourse to the same extent, and there is less pressure to sideline alternative perspectives. In the absence of strong interstate rivalry, local media and political actors are under less pressure to emphasize economic competitiveness and may feel freer to engage with a broader range of concerns, including the ethical, social, and regulatory implications of emerging technologies. This may help explain why critical or ethical frames do not experience the same decline as they do in high-competition settings.

One notable finding is the stability of technological or innovative frames across both high- and low-competition states. Unlike economic and ethical frames, which shifted in response to policy adoption, technological frames remained largely unchanged. This suggests that

innovation discourse is already embedded in the broader narrative surrounding autonomous vehicles, functioning as a consistent, background storyline. Because these frames tend to be descriptive and less politically charged, they are less influenced by competitive dynamics or elite signaling, reflecting a general cultural assumption of technological inevitability.

Implications

This study provides several important theoretical implications. First, this study advances existing theories of policy's framing effects, such as policy feedback, agenda-setting, and discursive institutionalism, by introducing a contingent perspective centered on interjurisdictional dynamics. While prior works tend treat the discursive effects of policy as uniform or internally determined, this study shows that the framing consequences of policy adoption are conditioned by the jurisdiction's competitive context. This relational reframing helps explain why similar policies can yield divergent narrative consequences across states, depending on their position within a broader field of regulatory competition. This approach adds an important external dimension to existing theories of policy framing, showing that the discursive impact of policy adoption depends not only on what is enacted, but also on where and under what strategic pressures it occurs.

Second, this study contributes to policy diffusion research by examining not just why policies are adopted, but how they shape public interpretation afterward. While extensive research has examined mechanisms of policy diffusion process (Dobbin et al. 2007), few studies have explored how these dynamics influence the discursive outcomes that follow policy adoption. By showing that competition not only explains when policies are adopted but also how they are framed afterward, this research enriches the understanding of diffusion's symbolic effects. States that adopt similar policies may still produce divergent public narratives depending

on their competitive context. This adds a discursive dimension to diffusion theory, highlighting the need to study post-adoption framing as an integral part of how policy diffusion unfolds.

By bridging two largely separate bodies of literature on policy framing and policy diffusion, this study opens new avenues for understanding how policy operates both symbolically and strategically. While framing theories tend to focus on how policies shape discourse within jurisdictions, and diffusion theories emphasize how policies spread across them, few works integrate these perspectives. Yet in practice, policies are both adopted in competitive interjurisdictional settings and interpreted through discursive processes shaped by those settings. Bringing these literatures into conversation reveals how competitive dynamics not only influence the timing and selection of policy adoption but also condition its meaning and public reception. This integrative approach offers a more comprehensive framework for analyzing how governance decisions shape, and are shaped by, both material interests and symbolic politics.

Third, this research has potential to enrich Science and Technology Studies (STS) by demonstrating how state-level policy adoption actively participates in the co-production of technological meaning and political order. While STS scholarship, particularly work on co-production (Jasanoff 2004), has shown that technologies and social institutions evolve together, this study extends that insight by showing how interstate competition conditions which meanings are elevated in public discourse. Rather than treating policy as a neutral response to innovation, the findings reveal that policy adoption operates as a discursive event. This highlights how institutional positioning within competitive governance environments helps co-produce not only the legitimacy of emerging technologies but also the sociopolitical imaginaries attached to them.

Finally, the findings contribute to frame theory by illuminating the conditions under which certain frames gain dominance while others are marginalized. Although the empirical

focus of this study is on autonomous vehicles and emerging technologies, the theoretical framework developed here extends to a wide range of contested policy domains, such as climate policy, immigration, education reform, or reproductive rights, where policy adoption, elite signaling, and interjurisdictional dynamics intersect. In these contexts, the interplay between jurisdictional rivalry and institutional signaling can shape which narratives gain prominence and which are marginalized.

Methodologically, this study demonstrates how state-of-the-art computational methods can be employed to examine framing dynamics at large scale. Sentence-BERT (SBERT) is especially effective for conducting frame analysis at the paragraph level, a unit of analysis that balances contextual richness with analytic precision in discourse research. Compared to traditional methods such as topic modeling or word embeddings, SBERT excels in handling short texts and capturing semantic nuance, making it well-suited for analyzing news content. Furthermore, this computational approach can be integrated with causal inference techniques to test theoretically grounded hypotheses about framing shifts over time. By combining advanced natural language processing with quasi-experimental designs, the study illustrates a scalable yet interpretively rich framework for analyzing discursive change.

For policymakers, the results highlight the importance of recognizing that the policy adoption can amplify certain narratives while suppressing others, particularly in high-competition environments. As states increasingly position themselves as innovation leaders to attract firms and capital, they may unintentionally foster public discourse that privileges promotional frames over critical deliberation. This has important implications for democratic governance, especially in areas like AI, autonomous vehicles, or biotechnology, where societal impacts are still unfolding. To ensure more balanced and inclusive public conversations, state

actors and media institutions should be mindful of how competitive pressures can narrow the framing of complex technologies. Practices such as inclusive stakeholder engagement, transparent risk communication, and institutional support for critical journalism can help ensure that ethical considerations remain visible alongside economic ambitions.

Limitations and Future Works

This study has several limitations that offer directions for future research. First, while it theorizes how competitive pressure shapes the discursive impact of policy adoption, it does not directly observe or test the mechanisms through which this influence unfolds. I proposed several plausible pathways, such as elite press strategies, media editorial decisions, or industry amplification, but the analysis does not disentangle which actors or mechanisms are most responsible for amplifying pro-innovation frames or suppressing ethical discourse under conditions of high competition. Is it elected officials' press strategies? Media editorial decisions? Industry stakeholder amplification? Disentangling the mechanism remains an important task for future empirical research. In addition, while the analysis centers on competitive pressure, it does not systematically test other mechanisms of diffusion, such as coercion, emulation or learning, that may also shape discursive responses. Future studies could employ comparative or experimental designs to disentangle these pathways.

The framework proposed here opens new avenues for policy literature. First, it can be extended to other contested issues, such as climate change, reproductive rights, or education reform, to assess whether the framing effects of policy adoption are similarly contingent. Second, future work might explore frame durability: Do discursive shifts persist over time, or are they ephemeral signals of political performance?

Chapter 4 Clash of Industries: How Evolving Inter-Industry Competition Structures Alliance Behavior in the Autonomous Vehicle Sector

4.1 Introduction

As technological innovation accelerates, an increasing number of historically distinct industries are drawn into deep collaboration, competition, and convergence (Jacobides 2022; Powell et al. 2005; Roth et al. 2019; Sick, Bröring, and von Raesfeld 2021). These are not simple episodes of market disruption sparked by peripheral challengers or startups. Rather, they involve direct collisions between two mature and powerful industries, each with its own institutional legacies, production infrastructures, and visions of future value creation (Greenwood et al. 2011). This raises an important and underexplored theoretical question: When two powerful established industries converge, what governs the formation and structure of inter-firm alliances?

This dynamic is especially visible in the case of autonomous vehicle (AV) development, where the century-old automotive industry has been challenged by the rise of dominant tech firms entering the mobility space (Anderson et al. 2016). Over the past decade, AV development has become a site of intense strategic activity across industry lines. As two industries converge, automotive OEMs, suppliers, tech giants, and tech startups have built a dense web of alliances, acquisitions, and co-development partnerships (Hess 2020). These collaborations blur traditional industry boundaries, with firms often acting simultaneously as collaborators, competitors, and suppliers (Burns 2018; Hannah and Eisenhardt 2018). This paper analyzes the structure of this

complex alliance network and investigates the underlying mechanisms that shape and organize partnerships as industries converge.

A long-standing body of research in strategic management, organizational theory, and economic sociology has provided frameworks for understanding why firms form alliances and how they govern them. Foundational studies explain alliances as tools for acquiring resources, reducing uncertainty, and managing inter-organizational dependencies (Ahuja et al. 2012; Barney 1991; Bergek et al. 2013; Gulati 1998; Pfeffer and Salancik 1978). Subsequent work extended these insights to contexts of technological disruption and environmental uncertainty, viewing alliances as vehicles for building dynamic capabilities, enabling firms to explore emerging domains, adapt to change, and maintain strategic flexibility (Beckman et al. 2004; Doz and Hamel 1998; Eisenhardt and Schoonhoven 1996; Teece 1996). While prior literature has deepened our understanding of alliance behavior under uncertainty, it has tended to focus on intra-industry dynamics or disruption from peripheral entrants. It is less equipped to explain alliance formation when two powerful industries converge.

Recent work in business ecosystem theory broadens the lens on alliance behavior by highlighting multi-actor collaboration across industry boundaries. These perspectives shift attention from dyadic ties to constellations of interdependent firms co-creating value through platforms, standards, and modular architectures (Adner 2017). Ecosystem research has illuminated how alliances facilitate strategic positioning within emerging value chains, enable market entry, and foster innovation across diverse participants (Jacobides et al. 2018). However, it falls short in two key respects. First, it tends to foreground harmony, complementarity, and coordination, offering limited attention to power struggle, contestation, or strategic rivalry. Second when it addresses power, it is typically conceptualized through hub-and-spoke models in

which a dominant orchestrator governs a network of weaker complementors. What remains undertheorized is when two powerful incumbents collide, each seeking influence over the same emerging space. These are not ecosystems coordinated by a single orchestrator, but contested terrains shaped by inter-industry struggle. As a result, current literatures in both alliance theory and ecosystem theory provide limited insight into how firms navigate alliance strategy when two established industries converge.

In this paper, I argue that inter-industry competition functions as a structuring logic that shapes alliance behavior during industry convergence. When two powerful industries collide, alliance formation is not merely about accessing complementary resources or positioning within an ecosystem, but it becomes part of a broader struggle over control, legitimacy, and the architecture of a shared future (Fligstein and McAdam 2012). Inter-industry competition introduces distinct pressures that influence how firms choose partners, configure collaborations, and navigate emerging interdependencies. Crucially, the nature of this competition is not static. As convergence deepens, the underlying logics of rivalry evolve, reconfiguring the pressures and rationales that drive alliance formation over time. This paper theorizes those evolving logics of inter-industry competition and analyzes how they shape alliance behavior in the context of deepening industry convergence.

To examine the structuring logics of inter-industry competition, I analyze the case of autonomous vehicle (AV) development, where the automotive and technology industries have experienced deep and sustained convergence from 2015. I trace how inter-industry competition evolves over time as convergence unfolds, identifying distinct logics that characterize this competition in different phases. Building on this characterization, I examine how these shifting logics shape the alliance behaviors of automotive original equipment manufacturers (OEMs) and

develop hypotheses accordingly. I focus on OEMs because they are consistently positioned at the center of inter-industry competition, facing sustained pressure to adapt alliance strategies as competitive dynamics evolve. Unlike tech firms, whose roles have shifted over time, OEMs remain stable incumbents, making them ideal for analyzing how alliance behavior responds to changing logics of competition.

I argue that, in the early phase of convergence, inter-industry competition in the autonomous vehicle (AV) sector was characterized by a displacement logic. Leading technology firms such as Waymo and Uber sought to redefine the future of mobility through fully autonomous systems and attempted to bypass traditional automakers by seizing control of the entire value chain. This ambition to displace automotive firms posed an existential threat to incumbent OEMs, shifting the core competitive arena from product differentiation to the struggle for strategic control over the future of mobility (Garikapati and Shetiya 2024). In response, OEMs were driven to adopt defensive alliance strategies aimed at rapidly acquiring critical technological capabilities. This dynamic significantly shaped both their choice of partners and the types of alliances they pursued.

As the convergence between the industries deepened, the displacement logic of competition gave way to a dependency logic of competition. Leading tech firms began to scale back their ambitions of fully replacing automakers, recognizing that hardware integration, safety validation, and regulatory compliance posed enduring challenges. A new cohort of tech giants, such as NVIDIA, Microsoft, and AWS, emerged at the center of the AV ecosystem by supplying critical infrastructure, including compute platforms, simulation tools, and cloud services. While interdependence between auto and tech firms increased, inter-industry competition did not disappear, but it transformed (Alvarez and Aoyama 2022). The core strategic tension shifted

from existential disruption to structural dependency. For OEMs, the threat was no longer exclusion from the AV field, but the risk of being relegated to subordinate roles within tech-dominated mobility ecosystems. In this context, OEMs are expected to structure their alliances, both in terms of partner choice and alliance form, to mitigate dependency and retain strategic autonomy.

To empirically test how inter-industry competition shapes alliance behavior across these phases, I collect an original dataset of alliances formed by automotive original equipment manufacturers (OEMs) in the U.S. autonomous vehicle (AV) sector from 2015 to 2024 and conduct a quantitative analysis focused on their alliance strategies. Using a hand-coded dataset of 517 alliances involving automotive OEMs, tech startups, infrastructure providers, and traditional suppliers, I classify each alliance by partner type, alliance form, and strategic function. To measure shifting inter-industry logics, I draw on patent data to construct time-varying indicators of displacement and dependency logics, based on the technological focus of AV-related patents. I then use multiple logistic regression models to test how changes in these competitive logics influence OEMs' alliance patterns, specifically their choice of partner types, alliance types, and redundancy strategies.

4.2 Theoretical Framework

4.2.1 Strategic Alliance Theories and Business Ecosystem Theories

A long-standing body of research in strategic management, organizational theory, and economic sociology has examined why firms form alliances, who they partner with, and how alliances shape performance. Foundational theories, including the Resource-Based View (Barney 1991), Resource Dependence Theory (Pfeffer and Salancik 1978), and network-based approaches (Podolny et al. 1996; Powell et al. 2005), emphasize that firms pursue alliances to

access complementary resources, share risks, and build capabilities that are difficult to develop internally (Eisenhardt and Schoonhoven 1996; Gulati 1995). At the same time, alliances are strategic responses to competition (Baum et al. 2010; Bothner 2003). Firms use alliances to navigate competitive environments, improve their relative positioning, influence industry standards, and gain flexibility in the face of strategic threats (Gimeno 2004; Hsieh and Vermeulen 2014; Rowley, Baum, and Shipilov 2004). In this view, alliances are embedded in broader competitive dynamics, where cooperation serves as a means of adaptation and advantage.

Alliance research has also extensively examined how firms use partnerships to navigate technological disruption and environmental uncertainty. Building on dynamic capability theories, scholars have emphasized that firms form, orchestrate, and reconfigure alliances as part of their broader strategies for adaptation and innovation (Helfat et al. 2007; Kale and Singh 2007; Teece 2007). Empirical studies show that firms use alliances to manage uncertainty (Li et al. 2008), explore emerging technologies (Rothaermel and Deeds 2004), and defend against technological obsolescence (Lavie 2006). Firms often form exploratory and exploitative alliances (March 1991) to navigate turbulence, accelerate innovation, and improve their strategic positioning in rapidly evolving competitive landscapes, such as biotech and information industries (Yamakawa, Yang, and Lin 2011; Yang, Zheng, and Zhao 2014). In these accounts, alliances serve as flexible mechanisms for sensing and responding to change, often in response to exogenous shocks or disruptive innovations introduced by peripheral or non-incumbent actors (Christensen 1997; Corbo, Corrado, and Ferriani 2024; Petzold, Schmidt, and Scaringella 2023).

Yet while these perspectives provide powerful insights, they face limitations when applied to settings where two powerful industries converge. Most alliance theories are grounded

in intra-industry dynamics, where firms operate under shared institutional logics and within common technological and regulatory frames (Sick, Bröring, and von Raesfeld 2021; Simms and Frishammar 2024). They tend to conceptualize disruption as an external shock acting on a unified field, rather than as a mutual incursion by adjacent sectors. Disruption is also typically attributed to peripheral entrants, such as startups, rather than established, resource-rich incumbents (Christensen 1997). As a result, existing theories struggle to account for alliance behavior when large, mature industries, such as automotive and tech, collide. In such cases, existing explanations are limited to capture the complexity of cross-industry convergence and its impact on alliance formation.

Growing literatures in business ecosystem offers great insights on increasingly complex and interdependent environments in which firms operate, especially in the context of industry convergence, digital transformation, and modular innovation. Rather than focusing on traditional industry boundaries, this perspective highlights how firms operate within interdependent systems of actors spanning multiple sectors (Adner 2017; Jacobides, Cennamo and Gawer 2018). These ecosystems involve a mix of complementors, orchestrators, and suppliers who jointly build new value propositions and reconfigure traditional industry boundaries. Ecosystem theory has been especially useful in capturing the logic of multi-actor coordination in emerging domains like smartphones, mobility-as-a-service, and cloud-based software (Bohnsack et al. 2024; Jacobides 2022). It recognizes that no single firm can innovate in isolation in complex technological environments, and that firms must navigate interdependencies both upstream and downstream. In this way, ecosystem theory has significantly advanced our understanding of industry convergence, particularly when it leads to the formation of new platforms, novel governance

structures, and expanded boundaries of value creation (Hannah and Eisenhardt 2018; Kapoor 2018).

Business ecosystem theory has offered valuable insights into how industries converge, but it is less equipped to explain what happens when two powerful industries compete for control of an emerging domain. Specifically, it faces two key limitations. First, ecosystem research has largely emphasized complementarity and coordination, portraying alliances as mechanisms for harmonization rather than contestation (Hurni, Huber, and Dibbern 2022). Even in dynamic settings, the focus tends to be on alignment, modularity, and interdependence, not on rivalry or strategic conflict. As a result, ecosystem theory often downplays the role of power, contestation, and rivalry in shaping alliance behavior. Second, even when power is addressed, it is typically modeled in hub-and-spoke terms, where a dominant orchestrator manages weaker complementors (Gawer and Henderson 2007; Hannah and Eisenhardt 2018). This framework is well-suited to asymmetrical control but falls short in contexts where multiple powerful industries collide, each bringing its own architectures, resources, and strategic visions. In such cases, ecosystems are not orchestrated but contested. Alliances become instruments for navigating power struggles and asserting control over the emerging field. These limitations make current ecosystem theory is limited to explain the alliance dynamics that unfold when two mature, resource-rich industries converge.

Therefore, while both strategic alliance theory and business ecosystem theory offer valuable insights into why firms form alliances, they fall short in explaining what unfolds when two powerful industries collide. In particular, they lack a framework for understanding the emergent dynamics of conflict, rivalry, and power struggle that characterize these inter-industry encounters.

4.2.2 Inter-Industry Competition as a Structuring Logic

This paper argues that inter-industry competition is a structuring force that shapes how firms navigate strategic choices when powerful industries collide. The convergence of mature industries is not simply a blending of competencies but a clash of architectures that generates profound uncertainty over future value creation and control (Schilling and Rozenshtein 2022). As a result, firms are no longer responding merely to environmental turbulence, but they are engaged in a struggle over the future architecture of the field, a contest not just over products and capabilities, but over control, standards, and the allocation of strategic positions (Fligstein and McAdam 2012).

Crucially, what makes inter-industry competition distinctive is the active engagement of powerful, established actors from both industries. Not all cross-industry interactions constitute competition. When a peripheral firm from an adjacent field enters, it may initiate inter-industry relationships or even disrupt the existing industrial order, but such cases do not amount to inter-industry competition. These actors are often niche players or disruptors without the institutional power to meaningfully challenge incumbents. In contrast, inter-industry competition arises when incumbent giants from each sector view one another as credible threats, each possessing the technological capacity, strategic intent, and field-level influence to reshape the emerging order. It is this symmetrical and reciprocal confrontation, where each actor recognizes the other as a rival with the potential to dominate, that defines genuine inter-industry competition.

Therefore, I view inter-industry competition functions as a structuring logic: a field-level orientation that shapes how firms interpret their position, define strategic priorities, and navigate alliance decisions during convergence. By “logic,” I do not mean a fully institutionalized belief system, but rather a shared and evolving interpretive frame that guides firm behavior. It

influences how firms perceive rivals, assess threats and opportunities, and determine how to act in a contested and shifting landscape (Fligstein and McAdam 2012). These competitive logics operate not at the level of individual transactions, but across categories of firms, shaping common patterns in how alliances are formed and structured in response to changing dynamics of power and control.

Inter-industry competition particularly serves as the key underlying logics that govern firm's alliance behavior. As convergence deepens, firms are not just building relationships for efficiency or innovation, they are navigating a shifting terrain of power and dependency (Bohnsack et al. 2024). The identity of the rival, the source of the threat, and the stakes of control are all redefined through inter-industry competition. Therefore, it shapes how firms perceive threats and opportunities. Alliances, in this context, become tools for field navigation: they are mechanisms not just for adaptation, but for positioning, influence, and strategic insulation (Hsu 2021). For incumbent firms, they may form alliances to access capabilities, but also to hedge against dominance, resist marginalization, or manage dependence on actors outside their historical domain. For, entrant firms, alliances provide legitimacy, access to existing technologies and foothold into a traditional market. The alliances they form, and how they form them, are structured by how they interpret the unfolding competitive relationship between industries.

Specifically, as inter-industry competition structures the alliance behaviors it influences the types of partners firms seek and the governance forms they prefer. When competition involves powerful actors with divergent architectures and control models, firms may prioritize alliances that provide visibility and bargaining power over those that simply offer access to technology (Karhu, Gustafsson, and Lyytinen 2018). For example, alliances may be structured

more flexibly to avoid lock-in, or deliberately duplicated across multiple partners to reduce reliance on any single actor (Gulati, Puranam, and Tushman 2012). These choices are not just strategic calculations but they are conditioned by how firms interpret the intentions and capabilities of rivals from the other industry. In short, the field is not only technologically fluid, but politically contested (Fligstein and McAdam 2012).

Importantly, the nature of inter-industry competition evolves as convergence proceeds. It is not a static logic. As the technologies develop, and inter industry relationships deepens, the logics of inter-industry competition that governs alliance behaviors could evolve. In those cases, firms' alliance behaviors are changing as the competitive logics shifts. Therefore, it is important to identify those evolving logics and characterize those shifts and examine how those can influence alliance behaviors.

4.3 Inter-industry Competition in AV Field: Displacement Logic to Dependency Logic

The field of autonomous vehicle (AV) development offers a compelling case for examining how inter-industry competition structures alliance behavior. AV development has drawn together two of the world's most powerful industries: the century-old automotive sector, with its deep expertise in manufacturing, systems engineering, and safety certification; and the technology industry, with its strengths in artificial intelligence, data platforms, and software-driven architectures (Garikapati and Shetiya 2024). The collision of these industries has produced a highly dynamic and contested field. Unlike conventional disruption by startups, AV development involves direct rivalry between incumbent giants, each bringing competing visions for the future of mobility (Alvarez León and Aoyama 2022). Over the past decade, this has resulted in a complex and evolving web of alliances, acquisitions, and co-development partnerships.

In the following sections, I identify and describe two distinct phases in the evolution of the AV industry, each defined by a dominant logic of inter-industry competition: an early phase structured by a displacement logic, and a later phase characterized by a dependency logic. These phases are not abstract theoretical categories but are empirically grounded in observed shifts in how competition unfolded over time. In the early displacement phase, technology firms such as Waymo (Google) and Uber sought to bypass traditional automotive incumbents by developing fully integrated AV platforms, aiming to control the entire stack and redefine the mobility value chain (Alvarez León and Aoyama 2022). In the later dependency phase, the competitive dynamic changed as tech firms increasingly entrenched themselves in critical infrastructure layers, such as chips, cloud, and simulation (Adner and Lieberman 2021). I argue that these two phases, structured respectively by displacement and dependency logics, systematically shape how firms form alliances and respond strategically within a converging industrial field.

To examine how shifting inter-industry logics shape alliance behavior, I focus on the strategic responses of automotive OEMs. As core incumbents in the automotive sector, OEMs occupy a central position in the evolving mobility ecosystem and are most directly exposed to inter-industry competition. Unlike auto suppliers, whose roles are often defined by modular production and long-term contracts, or tech startups, which depend on integration into larger platforms, OEMs sit at the strategic intersection where control over the vehicle, value chain, and customer interface is at stake (Anderson et al. 2016). This exposure gives them the strongest incentives to respond to shifts in competitive logic, and accordingly, they have emerged as the most active alliance builders in the AV domain (Murmann and Vogt 2022). Their combination of centrality, vulnerability, and strategic autonomy makes them ideal cases for observing how firms adapt to structurally distinct threats, initially from displacement, and later from dependency.

OEMs also offer continuity across both phases of industry convergence, making them well-suited for longitudinal analysis. In contrast, the role of tech firms has shifted significantly over time from early challengers like Waymo and Uber to infrastructure providers such as NVIDIA, Microsoft, and AWS (Alvarez León and Aoyama 2022). These role transitions complicate consistent analysis on the tech side. By focusing on OEMs, this study provides a coherent lens through which to trace how alliance strategies evolve in response to changing inter-industry dynamics. Future research should complement this by examining how tech firms adapt their own alliance behaviors as they transition from disruptors to embedded platform providers.

4.3.1 Early Phase (2015-2019): Displacement Logic

Prior to 2015, the automation of vehicles was primarily led by the automotive industry through incremental advances in Advanced Driver Assistance Systems (ADAS). These technologies, such as lane-keeping assist, adaptive cruise control, and emergency braking, were designed to enhance driver support, safety, and convenience, not to eliminate human control. Development was largely endogenous to the automotive sector, drawing on the engineering capabilities and legacy architectures of incumbent firms.

This trajectory was dramatically disrupted when Waymo (Google) and Uber entered the AV space, not to assist drivers, but to render them obsolete. Drawing on core strengths in AI, real-time perception, cloud infrastructure, and machine learning, these firms positioned themselves as leaders of a new mobility paradigm. Unlike traditional suppliers who aimed to support OEMs with modular components, these tech entrants pursued a much more ambitious strategy: the development of fully autonomous, vertically integrated mobility platforms designed to bypass automakers altogether (Alvarez León and Aoyama 2022; Burns 2018). Their goal extended beyond the vehicle itself. They sought to control the full AV value chain, from

software and sensor fusion to vehicle design and fleet operations. As Waymo stated in 2016, “We're not building a better car, we're building the world's most experienced driver.” This was more than a slogan. It reflected a deliberate attempt to redefine where innovation would occur and who would lead it in the future of mobility.

This phase was characterized by a distinct mode of inter-industry competition that I refer to as displacement logic. What defines this logic is the effort by powerful new entrants to displace incumbent firms by redefining what it means to compete in the domain of mobility. Rather than competing within established market categories (e.g., vehicle safety, performance, design), tech firms sought to reshape the very structure of the industry by repositioning mobility as a platform-based, service-centric field (Burns 2018). Their goal was not to be integrated into the existing industry but it was to render that structure obsolete. It was a struggle between two powerful, institutionalized industries, automotive and tech, each with its own logic of value creation, production, and control. At stake was the question of who would define the future of mobility (Stilgoe 2018). The core arena of competition was thus not price, product, or process but field control. Would the next generation of mobility be led by platform-based technology firms offering integrated services? Or by legacy OEMs maintaining their dominance through adaptation?

The tone of competition during this period was zero-sum and confrontational. Tech firms openly signaled their intent to displace incumbent automakers by redefining the contours of the mobility sector. This displacement was not rhetorical but it was operationalized through large-scale hiring of AV engineering teams, acquisition of key AV startups (e.g., Otto by Uber), and billion-dollar investments into proprietary AV stacks (Ferràs-Hernández, 2017). For OEMs, the implications were stark. If tech firms succeeded in capturing the central layers of the AV

ecosystem, they risked being relegated to the margins as undifferentiated hardware assemblers in a software-defined vehicle architecture.

This is what constituted an existential threat for OEMs. The displacement logic threatened the very identity and relevance of automotive incumbents. The concern was not merely that new competitors were entering the space, but that the rules of the field were being rewritten with OEMs cast in increasingly subordinate roles. As Ford's then-CEO Mark Fields noted in 2016, "We're not going to be just the sheet-metal bender in this new mobility world. We intend to own part of the brain, too." That statement captured the symbolic high stakes: to lose control over the vehicle's "brain" was to lose control over the industry.

OEMs saw the rise of tech firms in the AV space as a direct and urgent threat to their longstanding dominance in the mobility sector. This was not merely a technological disruption, but it was a fundamental challenge to their identity, authority, and future relevance. The displacement logic introduced by firms like Waymo and Uber implied that OEMs could lose control over the vehicle, the customer interface, and the broader innovation agenda. For OEMs, this became the most pressing competitive dynamic: a high-stakes struggle over who would define the future of mobility. Therefore, their primary strategic goal became securing access to relevant frontier technologies, particularly in AI, perception, and autonomous systems, to remain central system integrators rather than being relegated to the role of commodity hardware manufacturers. These moves were not just about catching up technologically; they were deliberate efforts to defend their institutional position in a field undergoing profound transformation.

Thus, the early phase defined by displacement logic reshaped the strategic landscape for all firms engaged in autonomous vehicle development. It established a competitive context in

which traditional industry boundaries were destabilized, and incumbents were forced to reassert their roles in a rapidly evolving field. In the following section, I describe the subsequent phase marked by a shift toward dependency logic. I then draw on these two phases to construct hypotheses specifically about how OEMs adapted their alliance strategies in response to these evolving forms of inter-industry competition.

4.3.2 Later Phase (2020-2024): Dependency Logic

As the autonomous vehicle (AV) field matured and convergence between the automotive and tech industries deepened, the nature of inter-industry competition began to shift. By the late 2010s, it became increasingly clear that early ambitions of full-stack disruption led by firms like Waymo and Uber were technologically premature and economically unviable in the short term (Tennant and Stilgoe 2021). Core bottlenecks in vehicle hardware, systems integration, safety validation, and regulatory alignment proved more persistent than anticipated. OEMs maintained control over these layers, drawing on decades of manufacturing expertise and embedded institutional capacity. Meanwhile, deploying full autonomy in real-world conditions proved far more complex and context-sensitive than early projections suggested (Alvarez León and Aoyama 2022). As a result, many tech firms either slowed, spun off, or recalibrated their AV efforts.

In this context, inter-industry competition entered a new phase, less about existential displacement and more about strategic interdependence. Rather than attempting to control the entire AV stack, a different group of tech firms, such as NVIDIA, Microsoft, and AWS, rose to prominence by embedding themselves at critical infrastructural layers (Alavarez León and Aoyama 2022; Schilling and Rozenshtein 2022). These firms did not seek to replace OEMs but to position themselves as indispensable providers of the compute, data, simulation, and AI infrastructure powering AV development. The result was a modularization of the AV value

chain: vehicle development became a layered ecosystem, and control increasingly shifted to those who dominated the infrastructural tiers.

I conceptualize this emergent phase as governed by a new form of inter-industry competition, what I call "dependency logic." Under this logic, rivalry between industries does not disappear; it is redirected. In contrast to the earlier emphasis on displacement, the central arena of competition between industries now lies in the control of critical infrastructure. The competitive question is no longer who manufactures the vehicle, but who defines the standards, owns the platforms, and governs access to the technological foundations of autonomy. Tech firms no longer seek to replace OEMs entirely. Instead, they position themselves as essential infrastructure providers by embedding their technologies deep within the value chain to shape innovation trajectories and create long-term dependence on their proprietary systems (Hurni, Huber, and Dibbern 2022).

For OEMs, the primary threat is no longer existential disruption but structural dependency. Crucially, infrastructure providers from the tech industry are not conventional suppliers. Firms like Microsoft, NVIDIA, and AWS are platform giants—armed with vast R&D budgets, control over adjacent markets, and strategic ambitions that extend well beyond the automotive sector. Their ability to set standards and exert influence across multiple layers of the value chain gives them disproportionate power to reshape the field. Much of the contemporary language surrounding business ecosystems suggests collaboration, mutual benefit, and co-evolution among interdependent actors. However, this discourse often masks underlying imbalances in power and control. While the rhetoric emphasizes partnership, the reality is that dominant tech firms increasingly dictate the terms of engagement. Inter-industry competition has not disappeared; it has simply been reframed. The struggle is no longer about who builds the

vehicle, but about who owns and governs the infrastructural rails that determine how innovation unfolds.

Under dependency logic, the OEM's key strategic concern is to manage dependency. They recognize the risks of lock-in, vendor dominance, and loss of architectural autonomy (Rothaermel 2001). To manage this new structural threat, OEMs have adopted strategies designed to reduce dependency on any single infrastructure provider. This includes diversifying alliances across functionally redundant partners, modularizing system architectures to maintain interoperability, investing in in-house capabilities to reduce reliance on external platforms, and selectively engaging in alliances that preserve strategic and architectural autonomy (Szalavetz 2024). In this phase, the goal is not rapid innovation or first-mover advantage, but strategic flexibility, bargaining power, and long-term control within an increasingly layered and interdependent ecosystem. As control over infrastructure becomes central to competitive positioning, OEMs prioritize moves that hedge dependency and safeguard their role in the emerging AV value chain.

In sum, dependency logic captures a distinct phase of inter-industry competition where the struggle for control has migrated from product and market domains to the infrastructural layer of technological development (Adner and Lieberman 2021; Jacobides et al. 2016). The competitive terrain is less visible but no less intense. For OEMs, the imperative is clear: remain at the center of the mobility ecosystem not by owning everything, but by ensuring they are not locked into tech giants. In the next section, I show how this structural logic reshaped the alliance strategies of OEMs, pushing them toward more flexible, portfolio-based, and autonomy-preserving forms of partnerships.

Table 4.1 compares key dimensions between displacement logic and dependency logic.

Table 4.1 Comparing Inter-industry Competition Logics

Dimensions	Displacement Logic	Dependence Logic
Temporal Period	2015-2019 (high uncertainty, full-stack ambitions, field redefinition)	2020-2024 (platform stabilization, dependency concerns, field layering)
Major Tech Giants	Waymo (Google), Uber, Apple	NVIDIA, AWS, Microsoft
Core Arena of Competition	Control over mobility (product, market, service integration)	Control over infrastructure (compute, cloud, AI stack, data, simulation)
Tone of Competition	Confrontational, zero-sum rivalry between tech giants and OEMs	Embedded, relational competition with asymmetrical power
Type of Threat	Existential threat: risk of being replaced or marginalized as mobility providers	Structural threat: risk of becoming dependent on powerful platform providers
Power Shift	Shifting full control to tech challengers who can render OEMs obsolete	Gradual erosion of autonomy through critical infrastructure dependence
OEM Strategic Concern	Losing control of the product, customer interface, and identity as mobility innovators	Losing architectural or strategic autonomy, vendor lock-in, inability to reconfigure
Alliance Function	Capability acquisition and field defense (to remain in control of AV innovation trajectory)	Dependency mitigation, flexibility retention, and multi-sourcing to avoid lock-in
Alliance Formation	Equity-based alliances, strategic investments, acquisitions, OEM–startup partnerships	Non-equity technology partnerships, co-development agreements, second-sourcing strategies

Note: This table summarizes the conceptual distinction between displacement and dependence logics of inter-industry competition. It contrasts the temporal, structural, and strategic dimensions of each logic and outlines OEMs' alliance motivations shift from capability acquisition to dependency mitigation.

4.3.3 Hypotheses on Alliance Behavior

Building on the preceding discussion of evolving inter-industry competition logics, I develop hypotheses about how these logics shape the alliance behavior of automotive OEMs. In particular, I focus on two dimensions of alliance behavior: the types of partners OEMs select and the types of alliances they form. For each hypothesis, I draw on existing theories of alliance formation and show how their underlying mechanisms become more or less salient under different inter-industry competition logics. The argument is that these logics function as structuring conditions, background forces that activate or suppress particular strategic responses, guiding how firms navigate collaboration in a contested and shifting field.

Displacement Logic Hypotheses

The displacement logic emerges when incumbent OEMs confront the risk of being overtaken by powerful tech firms. Drawing on the resource-based view and dynamic capabilities theories (Barney 1991; Teece 2007), OEMs recognize that their competitive advantage depends on acquiring valuable, rare, and hard-to-imitate capabilities that are increasingly located outside their organizational boundaries. In the AV context, these capabilities often reside in tech startups developing frontier AI, sensing, and mobility platforms. As a defensive response to this disruption, OEMs engage in alliances with startups to gain early access to critical technologies they lack internally. These alliances serve as a form of capability extension that aligns with RBV's emphasis on external sourcing when internal development is insufficient or too slow. These alliances are induced by the structural dynamics of inter-industry competition: they offer OEMs a way to mitigate displacement by embedding themselves in the technological vanguard and shaping the evolution of the AV stack. In this way, partnering with startups becomes a defensive yet proactive move to secure future relevance amid inter-sectoral rivalry.

Hypothesis 1: *When displacement logic is strong, OEMs are more likely to form alliances with tech startups in order to access rare and valuable capabilities that enhance their competitiveness.*

While displacement logic increases pressure to acquire external capabilities, not all OEMs are equally positioned to navigate this inter-industry competition effectively. In contexts where tech entrants threaten to redefine the terms of innovation, the ability to engage productively with startup partners becomes a strategic differentiator. The theory of absorptive capacity (Cohen and Levinthal 1990; Zahra and George 2002) helps explain variation in alliance behavior by highlighting the importance of internal R&D in recognizing, assimilating, and applying external knowledge. OEMs with greater R&D capabilities are better equipped to identify promising startup collaborators and to integrate new technologies into their development pipelines. These firms do not merely react to displacement pressures, they leverage inter-industry alliances as platforms for accelerated learning and innovation. In this way, absorptive capacity enhances the strategic utility of alliances under displacement logic by enabling OEMs to translate external ties into competitive advantage.

Hypothesis 2: *The positive relationship between displacement logic and the likelihood of forming alliances with tech startups will be stronger for OEMs with greater R&D capabilities.*

In early AV industry development, the fast pace of innovation and strategic uncertainty prompted OEMs to not only seek external capabilities but to secure them in a way that preserved influence and control. This was not just a matter of capability gaps but of long-term relevance and control over the future architecture of mobility. In this context, equity-based alliances, especially acquisitions and strategic investments (Wang and Jajac 2007), offered a mechanism for securing access to critical external capabilities while maintaining strategic influence over

their trajectory. Under the Resource-Based View, such deep alliances enable firms to internalize key resources, reduce the risk of knowledge leakage to competitors, and facilitate the transfer of complex, tacit know-how (Lavie 2006). Importantly, in the face of inter-industry competition, these alliances also serve as a hedge against marginalization. Equity ties allow OEMs to embed themselves in the innovation process and assert influence over the emerging AV stack, rather than being relegated to peripheral roles. The displacement logic thus leads OEMs to favor equity-based alliance forms as a way to anchor themselves in the future value chain, signal long-term commitment, and shape the direction of high-stakes technologies like AI.

Hypothesis 3: *When displacement logic is strong, OEMs are more likely to form equity-based alliances, such as acquisitions and strategic investments, in order to internalize critical capabilities.*

Dependency Logic Hypotheses

As the AV industry matured, the primary threat to incumbent OEMs shifted from the risk of displacement to the risk of structural dependency. In this later phase, dominant tech firms ceased competing as vertically integrated mobility providers and instead embedded themselves as infrastructure providers offering indispensable technologies, such as AI chips, simulation platforms, cloud environments, and mapping systems. These infrastructural capabilities became increasingly concentrated, granting tech firms significant structural power over downstream OEMs. From the perspective of Resource Dependence Theory (Pfeffer and Salancik 1978), OEMs responded by forming alliances with tech giants to access these essential technologies and manage the emerging asymmetry in power. These alliances were not capability-seeking in the traditional sense but necessity-driven attempts to ensure interoperability, technological

continuity, and access to evolving digital infrastructures that were too complex or costly to develop internally (Jacobides, Cennamo, and Gawer 2024).

Hypothesis 4: *When dependency logic is strong, OEMs are more likely to form alliances with tech giants in order to access critical infrastructure technologies such as computing, simulation, and cloud services.*

Although alliances with infrastructure providers were increasingly necessary, they exposed OEMs to the risks of vendor lock-in, reduced bargaining power, and loss of architectural autonomy. To manage these risks, OEMs sought governance forms that preserved flexibility. Drawing on Resource Dependence Theory, firms can mitigate power asymmetries not only by choosing partners strategically but also by structuring alliances in ways that limit vulnerability. Technology partnerships, non-equity collaborations focused on task-specific integration, offered a governance solution that enabled access while avoiding long-term entrenchment. These partnerships allowed OEMs to participate in business ecosystems (Adner 2017) without fully submitting to a single platform, thereby maintaining reconfigurability and modular independence (Adner and Lieberman 202). Compared to joint ventures or acquisitions, technology partnerships were particularly well-suited to infrastructure-oriented collaboration under high interdependence and evolving standards.

Hypothesis 5: *When dependency logic is strong, OEMs are more likely to form technology partnerships as a means of accessing critical infrastructure technologies while reducing the risks of structural dependence.*

Beyond alliance structure, OEMs also adopted portfolio-level strategies to mitigate strategic dependency. One such strategy was the deliberate formation of redundant alliances, multiple partnerships targeting the same functional domain (e.g., multiple cloud providers,

mapping platforms, or sensor technologies). This approach aligns with Resource Dependence Theory's emphasis on reducing external constraint through diversification (Casciaro and Piskorski 2005) and with ecosystem strategy literature, which highlights the value of modular redundancy for preserving system-level flexibility and avoiding platform lock-in (Scholten et al. 2023). Redundant alliances allowed OEMs to benchmark offerings, switch partners as needed, and preserve bargaining power in the face of concentrated supplier control. This behavior is especially rational in a platform ecosystem where standards are still evolving and infrastructure control may shift over time.

Hypothesis 6: *When dependency logic is strong, OEMs are more likely to form functionally redundant alliances, involving multiple partnerships with firms offering overlapping technologies, as a strategic hedge against structural dependency on dominant platform providers.*

4.4. Methodology

4.4.1 Data and Sample

This study investigates how inter-industry competition influences alliance formation by OEMs in the auto industry as the auto and tech industries converge to develop autonomous vehicle (AV) technologies. The dataset includes realized alliances, and the unit of analysis is the OEM–alliance–year: each observation represents a formal alliance initiated by an OEM with a specific partner in a given year. OEMs are treated as the focal firms, and all variables, including partner type, alliance type, and redundancy, are constructed from the OEM's point of view.

The sample includes 20 major global OEMs, selected based on a combination of three criteria: (1) sustained AV patenting activity, (2) repeated participation in AV-related alliances, and (3) consistent media visibility in the AV space (Alvarez León and Aoyama 2022; Ferràs-

Hernández et al. 2017). Firms were included if they met at least two of these criteria. I included non–U.S.-headquartered OEMs (e.g., Toyota, Honda, BMW, Hyundai) if they maintained an active AV presence within the U.S. market through subsidiaries, U.S. based R&D centers, local patenting activity, or partnerships with U.S. technology firms and universities. This approach reflects the reality that inter-industry competition in AV innovation is shaped by globally integrated yet locally embedded actors. While some of the OEMs are headquartered outside the United States, the dataset includes only alliances involving these firms that were conducted in the U.S. market or with U.S.-based partners. The focus on the U.S. based alliances allows for comparability in institutional context, competitive dynamics, and alliance documentation.

In addition to legacy automakers, the sample includes EV-focused OEMs such as Tesla, Rivian, and BYD. Though often viewed as disruptors, I classify them as OEMs due to their core function: the in-house design, production, and commercialization of complete vehicles (Bohnsack, Kolk, and Pinkse 2015). Unlike tech firms supplying software or infrastructure, these companies are vertically integrated manufacturers with branded products and regulatory compliance as automakers. Their AV strategies, while technologically distinctive, remain grounded in vehicle production and market competition. Including them reflects the auto industry's evolving composition, where new entrants share the organizational role of vehicle assembly and platform control. A control variable for electric OEMs is included in all models to account for their distinct characteristics.

Alliance data were compiled from multiple sources, including SDC Platinum, Crunchbase, Factiva[7], company press releases, industry reports, and financial filings (Schilling

[7] I used query to identify as many alliances as possible using Factiva because SDC platinum or other sources might not include the comprehensive list of alliances

2009). The dataset includes a range of formal collaborations relevant to AV innovation: acquisitions[8], investment, joint ventures, R&D collaborations, strategic alliances, pilot programs, licensing, and supplier agreements (Rothaermel and Boeker 2008). Only alliances with a clear AV-related focus were retained; alliances primarily focused on electric vehicle (EV) development, such as battery production, charging infrastructure, or electric drivetrains, were excluded. Each alliance is coded by year and month, partner identity, alliance type, stated motivation, and functional domain (e.g., chips, cloud services, mapping platforms). To accurately classify the functional domain of each alliance, I manually reviewed descriptive information from primary sources to identify the technological purpose and ensure consistency in coding across firms and years.

The dataset covers the period from 2015 to 2024, which corresponds to a critical window in the evolution of AV innovation. The dataset includes only alliances involving an OEM. Alliances formed exclusively between non-OEM firms, such as those between tech startups and tech giants, are excluded. While these partnerships are important in shaping the broader AV ecosystem, the present study is specifically designed to analyze how OEMs navigate inter-industry competitive pressures through their alliance strategies.

In addition to alliance data, several supplementary data sources were used to construct explanatory and control variables. Patent data were obtained from PatentsView, which provides disaggregated information on patent assignees, Cooperative Patent Classification (CPC) codes, and filing years (Kang and Motohashi 2020; Mukherjee and Wright 2021). These data were used

[8] To ensure organizational accuracy over time, acquired firms are treated as independent entities until the year of acquisition. From the acquisition year onward, any alliance involving the acquired firm is attributed to the acquiring firm. For example, Mobileye is treated as a standalone partner until its acquisition by Intel in 2017; after that point, Mobileye-related alliances are assigned to Intel. This rule preserves the temporal and organizational integrity of alliance observations.

to construct measures of inter-industry competition logics (displacement and dependence). Firm-level control variables, such as R&D expenditures, number of employees, and total revenue, were sourced from Compustat and reflect annual characteristics of the focal OEMs (Samila and Sorenson 2011). These variables help control for organizational capacity and alliance propensity independent of competitive dynamics.

4.4.2 Measures

Dependent Variables

The dependent variables capture three key dimensions of OEM alliance behavior that reflect how they responded to evolving inter-industry competition logics.

DV1: Partner Types

Each alliance partner is categorized into one of four mutually exclusive partner types based on the firm's industry origin and strategic role in the autonomous vehicle (AV) landscape:

(1) *Auto Supplier*: This category includes both traditional Tier 1 or Tier 2 suppliers and newer firms that focus on hardware-based solutions for vehicle systems. They originate from the automotive supply chain and typically contribute hardware-based capabilities such as sensors, braking systems, or embedded electronics. Examples include Bosch, Aptiv, and Continental.

(2) *OEM (Other Automakers)*: This category includes alliances between the focal OEM and another automotive manufacturer, including firms that are not part of the core OEM sample. In addition to large incumbents like Ford, Volkswagen, and GM, this category also includes smaller or regionally focused automakers and those excluded from the focal OEM sample but who appear in the dataset as partners in specific AV-related alliances.

(3) *Tech Startup*: Tech startups are younger, typically venture-backed technology firms that specialize in software, AI, perception systems, or autonomous driving stacks. These firms

lack a manufacturing legacy in the automotive sector and often emerge as potential disruptors or complementary innovators. Examples include Cruise, Aurora, Nuro, and Zoox.

(4) *Tech Giant*: Tech giants are large technology firms that influence AV development either by building full-stack autonomous driving systems (e.g., Waymo, Apple) or by supplying critical infrastructure technologies such as cloud platforms or AI chips (e.g., NVIDIA, Microsoft, Amazon). Firms are classified as tech giants based on their scale, platform control, and central role in enabling or competing with OEMs in AV development.

DV 2: Alliance Types

To empirically test the paper's hypotheses on the evolution of alliance strategies, each collaboration in the dataset was classified into a systematic, mutually exclusive typology. This categorization scheme is designed to capture the distinct strategic mechanisms and levels of commitment inherent in different alliance forms. The process begins with a primary distinction between equity and non-equity alliances, which are then further disaggregated based on their primary strategic intent. The five final categories are: Acquisition/Investment, Joint Venture, R&D Collaboration, Technology Partnership, and Strategic Alliance.

Equity-Based Alliances

Equity-based alliances involve a significant financial and structural commitment, signifying a deep level of integration or control. They are divided into two types:

(1) *Acquisition/Investment*: This category represents high-commitment alliances where one firm takes a direct equity stake in another. It combines (a) Acquisitions, involving the purchase of a controlling interest, and (b) Investments, including non-controlling strategic or venture capital stakes (e.g., Series A, B, C). These forms are grouped because they both serve as primary mechanisms for OEMs to gain deep access to external technology and talent.

(2) *Joint Venture (JV)*: This category is reserved for alliances that result in the creation of a new, legally distinct entity co-owned by two or more parent firms. This structure represents a profound commitment of capital and resources towards a shared operational goal and is distinct from simply taking a stake in an existing firm.

Non-Equity Alliances

Non-equity alliances are primarily contractual and are further distinguished by their primary strategic objective: invention, implementation, or commercialization.

(3) *Technology Partnership (Implementation-Focused)*: This category captures alliances where the primary goal is the downstream application, integration, or sourcing of existing or near-market technologies to create a specific product or service. The focus is on implementation rather than invention. This category pragmatically groups several SDC Platinum deal types that share an implementation-focused goal, including "Technology Sharing Agreements", "Licensing Agreements" (for technology), and technology-focused "Supplier Agreements". An R&D Agreement is also included here if its primary objective is implementation (e.g., co-engineering an integration) rather than foundational invention. Similarly, a Strategic Alliance is classified as a Technology Partnership if its scope is narrowly defined around a specific technology integration.

(4) *R&D Collaboration (Invention-Focused)*: This category includes alliances where the primary goal is upstream research, joint creation of novel technology, or the testing, validation, and demonstration of a technology or service on a limited scale. The focus is on both discovery/invention (often with longer time horizons) and real-world exploration or validation (through pilot programs and trials). This classification pragmatically groups activities that often fall under R&D Agreements in databases like SDC Platinum, as pilot

programs are frequently a component of a broader R&D effort. This alliance type is central to testing hypotheses related to early-phase capability building and technology validation.

(5) *Strategic Alliance (Commercial-Focused)*: This category includes broad, non-equity collaborations whose primary objectives are market-facing and commercial, rather than centered on technology development. This provides a distinct category for business-oriented partnerships. This classification corresponds to SDC Platinum deal types such as "Marketing Agreements", "Sales Agreements", and "Distribution Agreements".

I differentiated non-equity alliances based on their focus: Invention (R&D Collaboration), Implementation (Technology Partnership), or Commercialization (Strategic Alliance). This typology provides the necessary analytical precision to test how OEMs' specific alliance behaviors shift in response to the evolving dynamics of inter-industry competition. Table 4.2 summarizes the alliance types.

DV3: Alliance Redundancy

To examine how OEMs try to reduce dependency, I include a binary measure of alliance redundancy, whether a newly formed alliance overlaps in functional purpose with any prior alliance formed by the same OEM within the past three years. This variable reflects the theoretical expectation that, under conditions of infrastructural dependence, OEMs may deliberately form functionally redundant alliances as a form of risk mitigation or strategic hedging. Rather than relying exclusively on a single supplier for critical AV components (e.g., chipsets, cloud platforms), OEMs may diversify their dependencies by allying with multiple firms offering similar capabilities.

Redundancy is assessed at the alliance level. I adopt a hand-coded, qualitative approach based on the stated purpose and technological function of each alliance. For every alliance

Table 4.2 Alliance Type Categorization

Alliance Type	Equity vs. Non-Equity	Definition	SDC Platinum Deal Types
Acquisition/ Investment	Equity	High-commitment alliances where one firm takes a direct equity stake in another, combining full acquisitions and non-controlling investments.	M&A Deals, Private Placements, Venture Capital Rounds
Joint Venture (JV)	Equity	Creation of a new, legally distinct entity co-owned by two or more parent firms, representing a high structural and resource commitment.	Joint Venture
Technology Partnership	Non-Equity	(Implementation-Focused) Alliances with the primary goal of downstream application, integration, or sourcing of existing or near-market technologies.	Technology Sharing Agreements, Licensing Agreements (for technology), technology-focused Supplier Agreements
R&D Collaboration	Non-Equity	(Invention & Exploration-Focused) Alliances with the primary goal of upstream research, joint creation of novel technology, or the testing, validation, and demonstration of a technology or service on a limited scale. This category groups both foundational invention and real-world validation activities.	R&D Agreements (focused on foundational development)
Strategic Alliance	Non-Equity	(Commercial-Focused) Broad collaborations whose primary objectives are market-facing and commercial, rather than centered on technology development.	Marketing Agreements, Sales Agreements, Distribution Agreements

Note: The following table summarizes the five-part alliance typology used in this study. The categories are distinguished by their financial structure (Equity vs. Non-Equity) and their primary strategic objective, with corresponding examples of SDC Platinum deal types.

formed by an OEM in year t, I reviewed primary source materials (e.g., press releases, industry reports, Crunchbase, and Factiva entries) to determine the alliance's main function. I then compared this function to those of all prior alliances formed by the same OEM in the previous three years (i.e., t–1 to t–3). An alliance is coded as redundant = 1 if it shares a similar function with at least one prior alliance during that period (e.g., AV chip partnerships, simulation tools, or mapping systems); otherwise, it is coded as 0. For example, if Ford formed an alliance with NVIDIA in 2021 to integrate AV chipsets, and then allied with Qualcomm in 2023 for a similar chip-related purpose, the 2023 alliance is coded as redundant. If the 2023 Qualcomm alliance instead focused on a distinct function, such as V2X communication or OTA cloud services, it is not considered redundant even though they are the same company.

This measure captures strategic duplication of functionality, rather than simple partner or sector overlap. It provides a behaviorally grounded indicator of OEMs' risk management strategies in response to perceived dependency, and avoids the limitations of structural or typological redundancy measures that do not account for alliance content.

Independent Variable

The core task in measuring the independent variable is to capture two distinct inter-industry competitive logics: displacement and dependence. Displacement logic reflects the extent to which technology firms are developing vertically integrated, full-stack autonomous driving systems, posing a direct competitive threat to the traditional role of OEMs. In contrast, dependency logic captures the degree to which OEMs rely on technology firms for foundational infrastructure critical to AV development, such as chips, cloud computing platforms, and simulation tools.

Both logics are operationalized using U.S. patent data from 2012 to 2023. Patent data offers a structured and behaviorally grounded record of technological activity, enabling detailed analysis of how firms allocate R&D resources across different AV subdomains. Unlike financial indicators or subjective assessments, patent data is time-stamped, transparent, and scalable, making it a robust proxy for tracking shifts in the technological division of labor. It allows me to capture the strategic positioning of technology firms in the AV ecosystem, whether they are building complete autonomous platforms or supplying critical infrastructure, and thus serves as a field-level indicator of the competitive pressures OEMs confront.

To construct the displacement and dependency logic measures, I first collected all patents filed with the USPTO between 2012 and 2023 using a query-based search that combined autonomous vehicle–related keywords with Cooperative Patent Classification (CPC) codes. I then filtered this set to retain only those patents that included at least one AV-relevant CPC code, ensuring that the final dataset was specific to autonomous vehicle innovation. Targeted CPC codes included B60W (vehicle control), G05D (navigation/control), G06N (neural networks), H04L (communications), and related classifications covering perception, decision-making, and connectivity.

Each patent was linked to its corporate assignee and classified by industry using NAICS codes to distinguish between automotive firms and technology firms. Patents assigned to individuals, universities, or government agencies were excluded from the analysis. Because a single patent may include multiple CPC codes, I expanded the dataset to the patent–CPC code level to allow for disaggregated classification of technological functions.

To distinguish between displacement and dependency logics, CPC codes were categorized based on whether they support full-stack AV functionality or infrastructure-enabling

Table 4.3 Full Stack vs Infrastructure Patent CPC Codes

Primary Category	Functional Sub-Category	Representative CPC Codes & Their Role
Full stack	Perception & Prediction	B60W30/095 (Predicting other vehicles' paths), G06V20/56 (Seeing and understanding the environment with cameras), G01S13/867 (Fusing radar and camera data for robust perception), G01S17/931 (Using Lidar to prevent collisions), G06V20/597 (Identifying drivable road space from images), B60W40/105 (Anticipating the intentions of human drivers)
	Planning & Decision Making	B60W60/001 (Core task of planning and executing driving maneuvers), G06N5/022 (Using AI and rule-based logic to make driving decisions), B60W60/0018 (Managing the system's response to failures or bad weather)
	Control & Localization	G01C21/32 (Using an HD map to find the vehicle's exact position), G05D1/0214 (Physically controlling the vehicle to follow a planned path safely), B60W30/188 (Coordinating with other vehicles for cooperative driving like platooning), G06T7/73 (Using cameras to track the vehicle's own motion - visual odometry)
	Human-Machine Interface (HMI)	B60W60/005 (Managing the transfer of control between the AV and the driver), B60W50/029 (Monitoring the vehicle's health and ensuring functional safety)
Infrastructure	Hardware & Compute	G06F15/7807 (The specialized System-on-Chip [SoC] that runs the AV software), G06N3/063 (Dedicated AI accelerator hardware for neural networks), G01S7/481 (The core technology of the Lidar sensor itself), H04N23/90 (The core technology of advanced, intelligent vehicle cameras), H05K7/20863 (Specialized cooling systems for high-power AV computers)
	Software, Simulation & Dev Tools	G06F30/20 (Virtual environments for testing and validating AVs), G06F8/65 (Systems for deploying Over-the-Air [OTA] software updates to AV fleets), G06F11/3692 (Specialized tools for debugging complex, real-time AV software)
	Communication & Security	H04W4/40 (The foundational standard for V2X communication services), H04L63/08 (Systems for authenticating V2X messages to ensure they are trustworthy), H04W76/14 (The technology for direct vehicle-to-vehicle communication), H04W88/08 (The physical Roadside Units [RSUs] that form the V2X network)
	Mapping & Physical Infrastructure	G01C21/3804 (The process of creating and updating HD maps for AVs), G01C11/02 (The use of photogrammetry by mapping vehicles to build 3D maps), E01F9/30 (Physical road markings designed to be easily read by AV cameras)

technologies. Table 4.3 summarizes the CPC codes included in each category and provides their descriptions. Yearly measures were then constructed by calculating the proportion of each CPC category assigned to technology firms. Finally, I applied a three-year moving average (e.g., 2017–2019 for a 2020 observation) and lagged the measures by one year to smooth volatility and address simultaneity concerns.

Using these categories, I calculated annual proportions as follows:

Displacement Logic: the proportion of AV-related CPC codes classified as Full-Stack that were assigned to technology firms, relative to the total number of AV CPC code instances in a given year.

$$Displacement\ Logic_{\ t} = \frac{1}{3}\sum_{i=1}^{3}\frac{(Full\ Stack\ AV\ Patents\ by\ Tech\ Firms_{t-i})}{Total\ AV\ \ Patents_{t-i}}$$

Dependency Logic: the proportion of AV-related CPC codes classified as Infrastructure-Enabling that were assigned to technology firms, relative to the total.

$$Dependency\ Logic_{\ t} = \frac{1}{3}\sum_{i=1}^{3}\frac{(Infrastructure\ related\ AV\ Patents\ by\ Tech\ Firms_{t-i})}{Total\ AV\ \ Patents_{t-i}}$$

Because the two measures are conceptually distinct but empirically correlated, I combine them into a single index:

$$Net\ Logic_t = Dependency\ Logic_t - \ Displacement\ Logic_t$$

This Net Logic measure captures the relative dominance of infrastructural dependence over full-stack displacement in a given year. Positive values indicate that OEMs are operating in an environment where dependency logic is ascendant (i.e., they increasingly rely on tech firms for enabling technologies), whereas negative values reflect periods where displacement logic is stronger (i.e., tech firms are actively challenging OEMs with vertically integrated AV systems).

This variable provides a parsimonious, interpretable representation of shifting inter-industry competitive dynamics and serves as the key independent variable across all models.

Control Variables

To account for firm-level heterogeneity and yearly trends, I include a set of control variables that capture both organizational characteristics of OEMs and macro-level contextual factors.

At the firm level, I control for R&D intensity by including the log of each OEM's annual R&D spending, which reflects its internal absorptive capacity. I also include the log of the OEM's total number of employees to account for differences in organizational size. To control for baseline alliance propensity, I include two variables: the total number of alliances the OEM formed in the focal year (year t), and the total number of alliances it formed in the three preceding years (t–1 to t–3). These variables account for both immediate and cumulative alliance activity, capturing firm-specific engagement trajectories. Additionally, I include a binary indicator for whether the OEM is primarily focused on electric vehicle (EV) production, as EV-oriented firms may pursue different technological partnerships compared to traditional OEMs. Regional fixed effects are included to account for institutional and geographic variation in alliance practices. OEMs are classified into one of three regions, United States, Europe, or Asia, based on their global headquarters location.

To account for broader changes in the industry and macroeconomic environment, I include several year-level variables. First, I control for the log of the total number of AV-related patents filed in a given year, capturing the overall pace of technological innovation across the field. Second, I include the annual U.S. GDP growth rate as a proxy for macroeconomic conditions that may influence firms' alliance strategies. Third, I control for the total number of

Table 4.4 Variable Description

Variables	Descriptions
Dependent Variables	
DV1: Partner Type	
Auto Supplier	1 if the partner firm is a traditional automotive supplier (Tier 1 or Tier 2); 0 otherwise.
OEM	1 if the partner is another original equipment manufacturer (OEM); 0 otherwise.
Tech Startup	1 if the partner is a technology startup involved in autonomous vehicle development; 0 otherwise.
Tech Giant	1 if the partner is a major technology platform firm (e.g., Google, Amazon); 0 otherwise.
DV2: Alliance Type	
Acquisition/Investment	1 if the alliance is structured as an equity-based acquisition or strategic investment.
Joint Venture	1 if the alliance is structured as a legally incorporated joint venture.
Technology Partnership	1 if the alliance focuses on co-development or integration of core technologies.
Strategic Alliance	1 if the alliance is broadly strategic but not equity-based (e.g., co-branding, platform sharing).
R&D Collab/Pilot	1 if the alliance is an R&D agreement, test program, or pilot collaboration.
DV3: Redundant Alliance	1 if the alliance overlaps functionally with any other alliance formed by the OEM in the prior 3 years
Independent Variable	
Net Logic	Continuous variable constructed by subtracting dependence logic from displacement logic, based on the share of CPC-classified patents in full stack versus infrastructure categories.
Control Variables	
OEM Characteristics	
R&D Spending (log)	Log of the OEM's R&D spending (USD).
Employees (log)	Log of the OEM's total number of employees.
Total Alliances (t)	Total number of alliances formed by the OEM in year t.
Prior Alliances (3 Years)	Total number of alliances formed by the OEM in the prior three years.
Electric OEM	1 if the OEM is primarily focused on electric vehicle production; 0 otherwise.
Region	
US	1 if the OEM is headquartered in the United States; 0 otherwise.
Europe	1 if the OEM is headquartered in Europe; 0 otherwise.
Asia	1 if the OEM is headquartered in Asia; 0 otherwise.
Macro Change (Yearly level)	
Patents (log)	Log of the total number of autonomous vehicle patents filed in that year.
GDP Growth	Annual U.S. GDP growth rate (used as a proxy for macroeconomic context).
Industry Level Alliance	Total number of alliances formed in the AV industry in year t across all firms.

AV-related alliances formed across all firms in each year, which serves as a measure of ecosystem-level alliance density and allows me to separate firm-specific patterns from industry-wide trends.

These controls are included in all models to ensure that the estimated effects of inter-industry competition logics and alliance-level factors are not confounded by firm-level capabilities, industry trends, or external economic conditions.

Table 4.4 summarizes the descriptions and the measures of the variables.

4.4.3 Analytical Strategy

This study employs a series of logistic regression models to examine how inter-industry competition logics shape alliance behavior by automotive OEMs. All models use alliance-level observations as the unit of analysis, and the main independent variable is the yearly Net Logic score, capturing shifts in the balance between displacement and dependence pressures faced by OEMs.

I do not include year fixed effects in the models due to their strong correlation with the Net Logic measure, which is constructed from year-by-year patent distributions. Including year fixed effects would introduce multicollinearity and obscure the variation I seek to explain. To address this, I instead include macro-level year-specific controls, such as AV patent volume, GDP growth, and total industry alliance count, that capture broader temporal shifts without absorbing the variation in Net Logic itself. OEM fixed effects are included in selected models to control for unobserved heterogeneity across firms. Three sets of models are estimated, each corresponding to a distinct dimension of alliance behavior:

Partner Type Model: To assess how Net Logic influences the likelihood of collaborating with different types of partners, I estimate separate binary logistic regressions for each of the four

partner types: auto suppliers, other OEMs, tech startups, and tech giants. Each model predicts the probability that an alliance involved a given partner type, with the sample restricted to alliance events. Two specifications are estimated for each partner type. The first model includes only Net Logic and baseline controls. The second model adds an interaction term between Net Logic and OEM R&D spending, testing whether the effect of inter-industry logic varies by internal absorptive capacity.

Alliance Type Model: I use a second set of binary logistic regressions to analyze how Net Logic shapes the form of alliance. Separate models are estimated for each of the five alliance types: acquisition/investment, joint venture, technology partnership, strategic alliance, and R&D collaboration/pilot. This approach allows for fine-grained analysis of how OEMs structure external relationships under different competitive conditions.

Redundant Alliance Model: To test whether OEMs are more likely to form redundant alliances in response to increasing infrastructural dependence, I estimate a binary logistic regression where the dependent variable is whether the alliance overlaps functionally with a prior alliance by the same OEM in the past three years. The final model includes OEM fixed effects to account for unobserved firm-level differences in alliance strategy.

Across all models, standard errors are clustered at the OEM level to account for repeated observations within firms.

4.5. Results

4.5.1 Descriptive Patterns of Alliance Formation

Alliance-Level Descriptives

Table 4.5 reports summary statistics for all alliance-level variables. Consistent with the field's cross-industry character, alliances with tech startups (40%) and tech giants (36%) are s

Table 4.5 Descriptive Statistics

Variables	Mean	S.D	Min	Max	N
Net Logic	3.39	7.66	-16	9	517
Partner: Auto Supplier	0.12	0.32	0	1	517
Partner: OEM	0.11	0.31	0	1	517
Partner: Tech Startup	0.40	0.49	0	1	517
Partner: Tech Giant	0.36	0.48	0	1	517
Alliance: Acquisition/Invest	0.21	0.41	0	1	517
Alliance: Joint Venture	0.09	0.29	0	1	517
Alliance: Technology Partner	0.24	0.42	0	1	517
Alliance: Strategic Alliance	0.20	0.40	0	1	517
Alliance: R&D Collab/Pilot	0.26	0.44	0	1	517
Redundant Alliance	0.31	0.46	0	1	517
R&D Spending (log)	9.63	0.36	8.65	10.30	517
Employees (log)	5.13	0.41	3.27	5.85	517
Total Alliances (t)	4.80	3.14	1	14	517
Prior Alliances (3 Years)	8.42	6.28	0	27	517
Patents (log)	7.52	0.77	5.84	8.30	517
GDP Growth	2.49	1.95	-2.2	6.3	517
Industry Level Alliance	61.26	21.86	21	96	517
Region: US	0.22	0.42	0	1	517
Region: Europe	0.37	0.48	0	1	517
Region: Asia	0.41	0.49	0	1	517
Electric OEM	0.09	0.29	0	1	517

Note: Descriptive statistics for all alliance-level variables (N = 517). Binary variables represent proportions; continuous variables are reported in their logged or raw forms as specified. Net Logic captures the relative dominance of dependence over displacement in a given year.

substantially more common than those with auto suppliers (12%) or other OEMs (11%). This distribution demonstrates that the autonomous vehicle (AV) sector is shaped more by inter-industry collaboration than by traditional automotive coordination. The most prevalent alliance forms are R&D collaborations or pilots (26%), technology partnerships (24%), and strategic alliances (20%), while acquisitions and investments account for 21% of the sample. The low prevalence of joint ventures (9%) suggests that OEMs generally prefer more modular or flexible forms of coordination, particularly when engaging with partners outside their legacy industry.

Table 4.6 presents bivariate correlations among continuous variables. Net Logic is positively correlated with patent volume (r = 0.57) and industry-wide alliance density (r = 0.54), suggesting that periods marked by infrastructural dependence are also associated with broader technological activity and intensified field-level collaboration. Notably, OEMs' prior alliance history is positively correlated with Net Logic, consistent with the idea that firms become increasingly embedded in platform-dependent alliance networks over time.

Table 4.6 Correlation Matrix between Continuous Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Net Logic	1.000							
(2) R&D Spending	0.060	1.000						
(3) Employee (log)	0.027	0.746	1.000					
(4) Alliance Year (t)	0.271	0.227	0.158	1.000				
(5) Prior 3 Y Alliances	0.512	0.294	0.246	0.569	1.000			
(6) Total Patents (log)	0.566	-0.019	0.002	-0.104	0.131	1.000		
(7) GDP Growth	0.047	0.083	0.061	0.106	0.046	-0.014	1.000	
(8) Industry Alliance	0.540	0.110	0.046	0.459	0.361	-0.198	0.197	1.000

Partner Types/Alliance Types Trends Over Time

Figure 4.1 displays the annual distribution of alliances by partner type. Several trends are evident. First, tech startups and tech giants consistently dominate alliance activity, underscoring the persistent role of inter-industry alliances. Tech startup alliances increased sharply between 2016 and 2019, a period characterized by displacement threats as new entrants challenged incumbent OEMs. After 2020, however, growth in tech giant partnerships outpaces startup activity, reflecting a broader shift toward infrastructural reliance. Second, the absolute number of alliances rises sharply in 2024, possibly reflecting renewed investment following a plateau during 2020–2022, or the growing standardization of AV development inputs. In contrast, alliances with auto suppliers and OEMs remain relatively stable and low in volume, suggesting that intra-industry collaboration remains a secondary strategy.

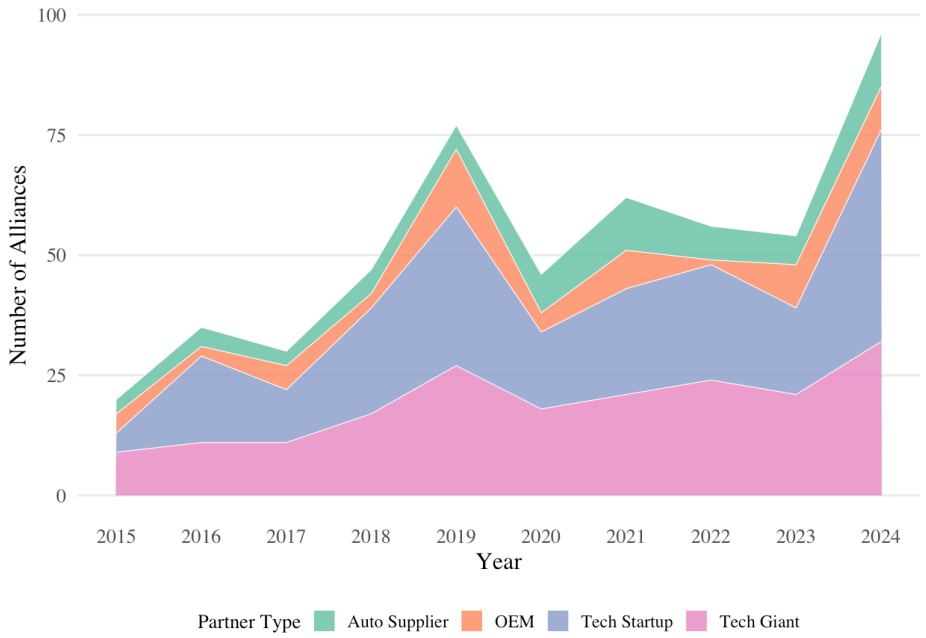


Figure 4.1 Annual trends in partner types (2015–2024)

Figure 4.2 reveals a parallel shift in the structural form of alliances. In the early years (2015–2019), OEMs were more likely to pursue equity-based alliances, especially acquisitions

and investments. This pattern is consistent with displacement logic, where firms seek control over external capabilities to preempt disruption. In contrast, the period after 2020 sees a marked increase in technology partnerships, which emerge as the most common alliance form by 2024. This trend is consistent with dependency logic, in which OEMs integrate external infrastructure technologies through modular, non-equity collaborations that offer access without ownership. The relative decline in acquisitions and investments during this phase further supports the interpretation of a structural shift from absorptive to integrative strategies.

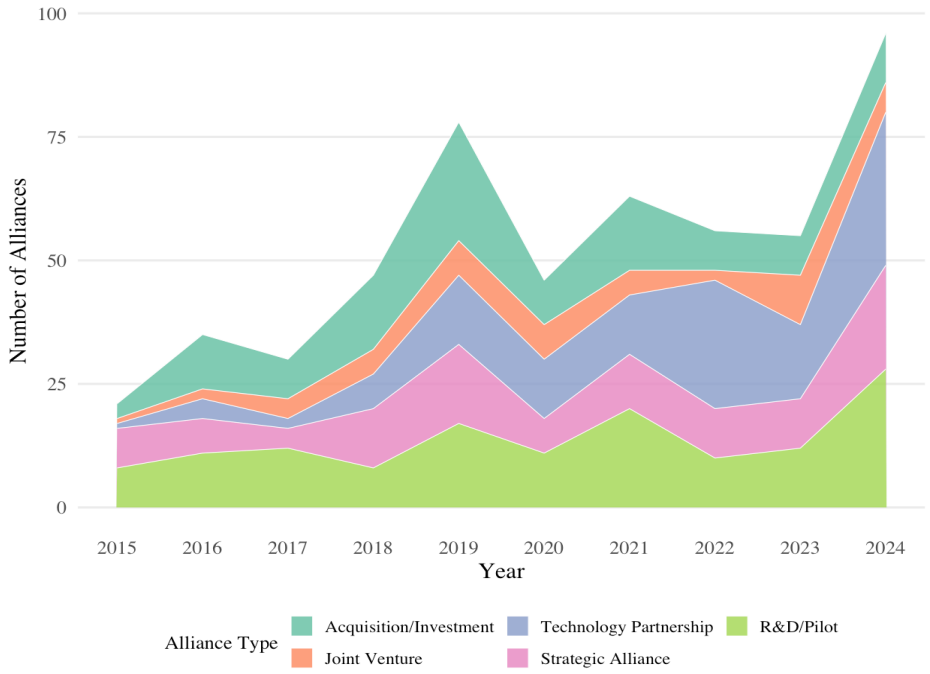


Figure 4.2 Annual trends in alliance types (2015–2024)

Phase Comparisons: Displacement vs. Dependence

Table 4.7 compares alliance and partner types across two analytically defined periods: the displacement phase (2015–2019) and the dependence phase (2020–2024). The data reveal a clear reconfiguration of alliance types over time. Among partner types, by contrast, the distribution

remains more stable. Tech startup alliances decline slightly in relative share (from 42% to 39%) while tech giant partnerships increase modestly (from 36% to 37%). While the absolute number of alliances grows in both categories, the relative shift in partner types is less pronounced than the shift in alliance structure. Among alliance types, acquisitions and investments fall from 29% to 16%, while technology partnerships more than double, rising from 13% to 31% of all alliances. The relative shares of R&D/pilot and strategic alliances remain stable, suggesting that experimentation and exploratory collaboration persist across both phases.

Table 4.7 Alliance and Partner Type Percentage (Displacement to Dependence)

Type	Category	Displacement (2015–2019)		Dependency (2020–2024)	
		Freq.	%	Freq.	%
Partner Type	Auto Supplier	20	9.57	43	13.69
	OEM	26	12.44	31	9.87
	Tech Startup	88	42.11	124	39.49
	Tech Giant	75	35.89	116	36.94
	Total	209	100	314	100
Alliance Type	Acquisition/Investment	61	29.19	50	15.92
	Joint Venture	19	9.09	30	9.55
	Technology Partnership	28	13.4	96	30.57
	Strategic Alliance	46	22.01	59	18.79
	R&D/Pilot	55	26.32	79	25.16
	Total	209	100	314	100

Note: This table compares the distribution of alliance types and partner types between the displacement phase (2015–2019) and the dependence phase (2020–2024). Percentages reflect each category's share of total alliances in each time period.

Taken together, these patterns suggest that OEMs have responded to changing competitive logics primarily by altering how they collaborate, through changes in alliance types, rather than fundamentally transforming who they collaborate with. This indicates that the AV

industry's evolution from displacement to dependence is reflected more clearly in shifts toward modular, non-equity partnerships than in a wholesale reordering of inter-organizational relationships.

4.5.2 Statistical Results

Partner Type Analysis

Table 4.8 presents the results from logistic regression models predicting the likelihood that an OEM forms an alliance with each of four partner types: tech startups, tech giants, auto suppliers, and other OEMs. Two models are estimated per partner type: a baseline model and a second model that includes an interaction between Net Logic and R&D spending. This section focuses on the theoretical predictions related to displacement and dependency logics.

The results for tech startup alliances show that Net Logic, taken alone, does not exert a statistically significant effect on the likelihood of forming an alliance with a startup according to model 1. This null finding provides no support for Hypothesis 1, which predicted that stronger displacement logic would increase the likelihood of startup collaboration. However, in model 2, the coefficient for the interaction term between Net Logic and R&D spending is negative and statistically significant ($\beta = –0.145$, $p < 0.001$), offering strong support for Hypothesis 2.

The marginal effects plot in Figure 4.3 illustrates how the relationship between Net Logic and the likelihood of partnering with tech startups varies by a firm's internal R&D capacity. For OEMs with high R&D intensity (e.g., log R&D = 10), the probability of partnering with a tech startup is highest when displacement logic dominates (i.e., Net Logic is strongly negative), approaching 70%. However, as Net Logic shifts toward dependence, their likelihood of startup alliances declines steadily, falling below 30%. In contrast, low-R&D firms (e.g., log R&D = 8.5) are least likely to form startup partnerships under strong displacement pressure, with

Table 4.8 Binary logistic regressions predicting partner type (2015-2024)

	Tech Startup		Tech Giant		Auto Supplier		OEM	
Variables	Model 1	Model2	Model 1	Model 2	Model1	Model2	Model1	Model2
Net Logic	-0.035	1.366***	-0.005	-0.974*	0.020	-0.558	0.054	-0.025
	(0.025)	(0.382)	(0.025)	(0.469)	(0.041)	(0.535)	(0.034)	(0.605)
R&D Spending (log)	0.041	0.589	0.504	0.169	-0.251	-0.479	-0.192	-0.214
	(0.364)	(0.425)	(0.393)	(0.470)	(0.601)	(0.624)	(0.771)	(0.841)
Net Logic X R&D Spending		-0.145***		0.101*		0.061		0.008
		(0.038)		(0.049)		(0.054)		(0.063)
Employee (log)	0.445	0.480	-0.324	-0.365	-0.224	-0.261	-0.239	-0.241
	(0.350)	(0.327)	(0.384)	(0.391)	(0.565)	(0.572)	(0.735)	(0.732)
Alliance Types (Ref: R&D)								
Acquisition/Invest	2.097***	2.112***	-2.217***	-2.202***	-0.908	-0.895	-0.482	-0.482
	(0.260)	(0.261)	(0.477)	(0.448)	(0.474)	(0.492)	(0.449)	(0.450)
Joint Venture	-0.196	-0.163	-1.297**	-1.360**	-0.374	-0.392	2.368***	2.363***
	(0.374)	(0.384)	(0.430)	(0.442)	(0.933)	(0.918)	(0.362)	(0.363)
Technology Partnership	-0.216	-0.192	0.623*	0.595*	-0.445	-0.463	-1.401	-1.406
	(0.267)	(0.274)	(0.261)	(0.268)	(0.539)	(0.532)	(0.803)	(0.805)
Strategic Alliance	-0.260	-0.174	0.279	0.204	-0.695	-0.732	0.724	0.715
	(0.359)	(0.359)	(0.360)	(0.371)	(0.415)	(0.399)	(0.541)	(0.538)
N of Alliances (t)	0.015	0.008	0.023	0.030	-0.021	-0.016	-0.084	-0.085
	(0.038)	(0.039)	(0.037)	(0.038)	(0.032)	(0.034)	(0.095)	(0.095)
Prior Alliances (3 years)	0.012	0.017	-0.006	-0.011	0.031	0.029	-0.088*	-0.089*
	(0.020)	(0.022)	(0.017)	(0.019)	(0.028)	(0.027)	(0.044)	(0.044)
Patents (log)	0.116	-0.000	0.134	0.210	-0.114	-0.084	-0.266	-0.257
	(0.223)	(0.227)	(0.221)	(0.215)	(0.266)	(0.270)	(0.328)	(0.316)
GDP Growth	-0.060	-0.039	-0.006	-0.022	0.050	0.043	0.104	0.102
	(0.049)	(0.048)	(0.047)	(0.049)	(0.097)	(0.099)	(0.100)	(0.097)
Total AV Alliance	0.014	0.010	-0.009	-0.006	-0.012	-0.011	0.007	0.007
	(0.008)	(0.009)	(0.008)	(0.007)	(0.011)	(0.011)	(0.014)	(0.014)

Region (Ref: US)								
Europe	0.492*	0.601*	-0.627*	-0.704*	1.038***	1.011**	-0.950*	-0.971*
	(0.223)	(0.255)	(0.266)	(0.273)	(0.315)	(0.323)	(0.422)	(0.437)
Asia	0.936**	1.096***	-0.541*	-0.648*	-0.136	-0.196	-0.657	-0.687
	(0.306)	(0.328)	(0.250)	(0.269)	(0.489)	(0.504)	(0.480)	(0.485)
Electric OEM	0.023	0.028	0.111	0.112	0.678	0.657	-0.894	-0.892
	(0.398)	(0.362)	(0.318)	(0.317)	(0.904)	(0.880)	(0.504)	(0.503)
Constant	-5.549	-10.071**	-3.628	-0.810	2.660	4.787	3.416	3.572
	(3.312)	(3.535)	(2.932)	(3.388)	(5.190)	(5.122)	(6.141)	(6.683)
N	517	517	517	517	517	517	517	517
R-Squared	0.161	0.177	0.144	0.153	0.062	0.065	0.206	0.206

Note: Dependent variables indicate whether an alliance involved a specific partner type. Net Logic and its interaction with R&D Spending test Hypotheses 1–2 and 4. Standard errors clustered by OEM.
**p < .05, **p < .01, ***p < .001 (two-tailed tests.).*

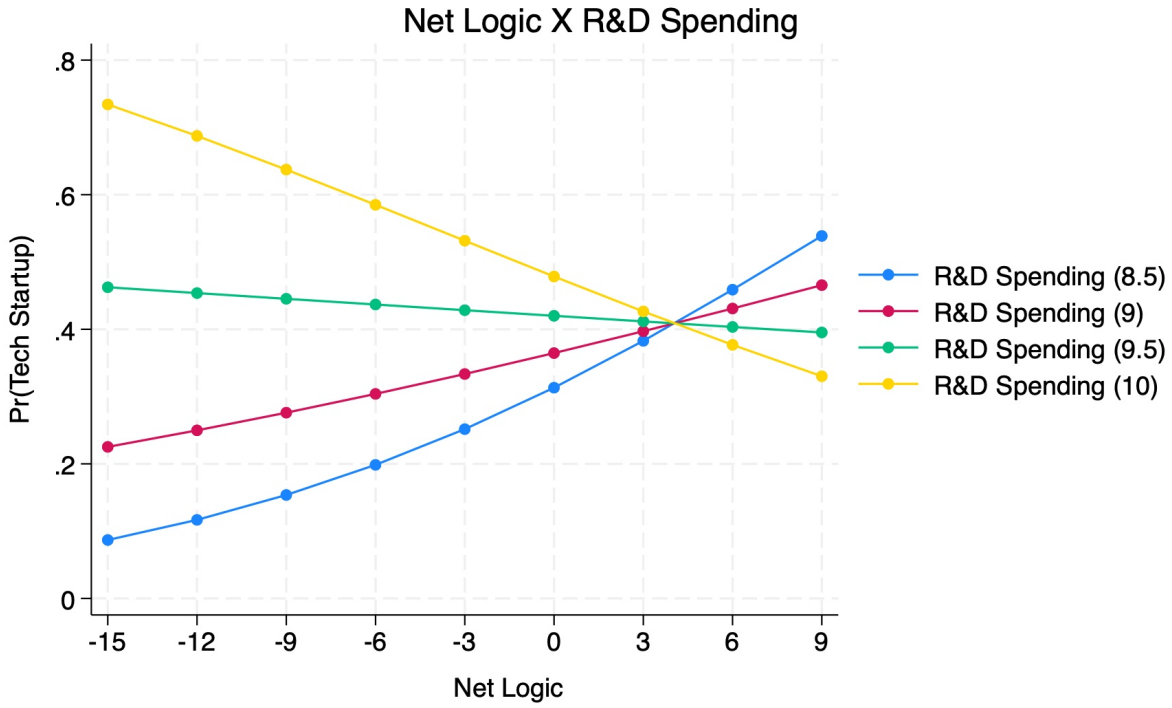


Figure 4.3 Marginal predicted probabilities of partner type by net logic and R&D spending

probabilities below 10%, but their propensity increases under dependence, rising to over 50%. This interaction suggests that the strategic value of startup alliances is interpreted differently depending on internal capabilities. High-capacity firms leverage startups as complementary innovation sources when facing disruptive threats, while low-capacity firms increasingly turn to startups under dependence, perhaps as a way to fill critical technological gaps when constrained by reliance on dominant platforms.

The results for tech giant alliances do not support Hypothesis 4 in its baseline form. In Model 1, Net Logic is not significantly associated with the likelihood of forming an alliance with a tech giant ($\beta = -0.005$, $p > 0.1$). This indicates that shifts in inter-industry competitive logic, when taken alone, do not predict greater engagement with dominant infrastructure providers. However, Model 2 reveals a positive and statistically significant interaction between Net Logic and R&D spending ($\beta = 0.101$, $p < 0.05$), suggesting conditional support for H4. Specifically, as dependency logic increases, OEMs with greater R&D capacity become more likely to form alliances with tech giants. In contrast, Net Logic has little effect on partnership likelihood among lower-R&D firms. This finding implies that responding to infrastructural dependence through alliance formation may require a threshold level of absorptive capacity. High-capacity firms are better positioned to manage the complexity and strategic risk of integrating external platforms such as AI chips, cloud services, or simulation tools.

For predicting other partner types such as auto supplier and other OEMs, no significant effects of Net Logic or its interaction with R&D spending are observed in the models. This pattern suggests that intra-industry alliances are less responsive to shifts in inter-industry competitive logic, and may instead be shaped by structural complementarities or firm histories. Notably, the likelihood of forming an alliance with another OEM is strongly associated with

joint ventures ($\beta = 2.368$, $p < 0.001$), indicating that such alliances often involve deep, equity-based collaboration, possibly for shared platform development or strategic mobility services.

Patterns across alliance structures further illuminate how OEMs tailor collaboration strategies to different partner types. When the dependent variable is tech startup alliances, acquisitions and investments are strongly and positively associated ($\beta = 2.112$, $p < 0.001$), suggesting that OEMs often pursue equity-based control strategies when engaging with startups. This pattern supports the idea that, under displacement logic, OEMs seek not only access to capabilities but also strategic control over emerging technologies through deeper integration mechanisms.

In contrast, tech giant alliances are negatively associated with equity-based forms: both acquisitions/investments ($\beta = –2.202$, $p < 0.001$) and joint ventures ($\beta = –1.360$, $p < 0.01$) are significantly less likely. Instead, tech giant alliances are positively associated with technology partnerships ($\beta = 0.595$, $p < 0.05$), a more flexible, non-equity form that allows OEMs to access critical infrastructure technologies, such as cloud platforms or AI chips, without deep organizational entanglement. This aligns closely with the logic of dependence management, where firms aim to reduce lock-in while integrating external platforms.

These alliance structure patterns reinforce the broader theoretical claim that who firms partner with is closely linked to how they structure the alliance, and that this linkage is shaped by the nature of inter-industry versus intra-industry dynamics.

Geographic patterns are pronounced. European and Asian OEMs are significantly more likely than U.S. OEMs to partner with tech startups (Europe: $\beta = 0.492$, $p < 0.05$; Asia: $\beta = 0.936$, $p < 0.01$), and European OEMs are also more likely to ally with tech giants ($\beta = –0.627$, p

< 0.05). These differences may reflect regional differences in innovation ecosystems, regulatory frameworks, or strategic orientation toward technological outsourcing.

Alliance Type Analysis

Table 4.9 presents logistic regression models predicting the alliance types formed by OEMs. These models assess how shifts in inter-industry competition logic shape the way OEMs structure their alliances. Model 1 shows that Net Logic is negatively and significantly associated with the likelihood of forming an acquisition or investment alliance ($\beta = –0.159$, $p < 0.001$). Because lower Net Logic values indicate stronger displacement logic, this finding supports Hypothesis 3, which predicted that OEMs facing disruptive threats would favor deeper, equity-based collaboration forms in order to secure control over critical external capabilities.

Further, acquisition/investment alliances are significantly more likely when the OEM is partnering with tech startups ($\beta = 1.460$, $p < 0.001$), and significantly less likely when partnering with tech giants ($\beta = –1.336$, $p < 0.05$). This pattern underscores the notion that equity-based alliances are a strategic response to displacement: OEMs invest in or acquire startups to absorb innovation and preempt competitive threats, while avoiding equity entanglement with dominant platform providers.

Model 3 shows that Net Logic is positively and significantly associated with the likelihood of forming a technology partnership ($\beta = 0.169$, $p < 0.001$), offering strong support for Hypothesis 5. This finding indicates that under dependency logic, alliances tend to take the form of structured, non-equity partnerships. These arrangements allow OEMs to access platform technologies such as AI chips, cloud ecosystems, or proprietary software while minimizing the risks of over-dependence or strategic lock-in. Technology partnerships are less likely when the partner is an auto supplier ($\beta = –1.948$, $p < 0.01$), and are significantly more likely among

Table 4.9 Binary logistic regressions predicting alliance types (2015-2024)

	Model 1 Acquisition/Invest	Model 2 Joint Venture	Model 3 Technology Partnership	Model 4 Strategic Alliance	Model 5 R&D Collaboration
Net Logic	-0.159***	0.029	0.169***	0.002	-0.008
	(0.036)	(0.053)	(0.046)	(0.033)	(0.043)
R&D Spending (log)	1.686*	-1.033	-0.753	-0.239	-0.304
	(0.760)	(0.546)	(0.712)	(0.767)	(0.630)
Employee (log)	-1.272	1.810**	0.514	-0.300	0.312
	(0.707)	(0.585)	(0.515)	(0.725)	(0.430)
Partner Types (Ref: OEM)					
Auto Supplier	-0.528	1.904*	-1.948**	0.643	-0.933*
	(0.622)	(0.803)	(0.755)	(0.590)	(0.448)
Tech Startup	1.460***	-0.366	-0.464	-0.167	-0.808*
	(0.399)	(0.971)	(0.429)	(0.420)	(0.365)
Tech Giant	-1.336*	-0.871	0.551	0.654	-0.336
	(0.613)	(0.966)	(0.448)	(0.438)	(0.427)
N of Alliances (t)	0.011	-0.014	0.042	-0.004	-0.125
	(0.067)	(0.064)	(0.057)	(0.039)	(0.094)
Prior Alliances (3 years)	0.096*	0.020	-0.024	-0.042	-0.032
	(0.038)	(0.023)	(0.025)	(0.029)	(0.034)
Patents (log)	1.180***	0.310	-0.556*	-0.291	-0.242
	(0.214)	(0.254)	(0.241)	(0.177)	(0.227)
GDP Growth	0.005	-0.076	-0.035	0.035	0.029
	(0.046)	(0.073)	(0.042)	(0.051)	(0.048)
Industry Level Alliance	0.014	-0.017	-0.013	0.003	0.006
	(0.013)	(0.012)	(0.009)	(0.007)	(0.012)
Region (Ref: US)					
Europe	-0.532	0.284	-0.825	1.201	-0.297
	(0.414)	(0.345)	(0.468)	(0.707)	(0.437)
Asia	0.081	-0.017	-1.237**	0.396	0.288
	(0.478)	(0.423)	(0.469)	(0.760)	(0.512)
Electric OEM	0.024	0.170	1.161***	-1.918	-1.023

	(0.833)	(0.581)	(0.343)	(0.979)	(0.527)
Constant	-23.607***	-0.886	10.771	3.345	1.712
	(4.407)	(5.515)	(6.127)	(5.524)	(4.553)
N	517	517	517	517	517
R-Squared	0.268	0.162	0.190	0.089	0.040

Note: Dependent variables indicate whether an alliance took a specific structural form. Net Logic tests Hypotheses 3 and 5. Partner type covariates account for the relationship between who OEMs partner with and how they structure alliances. Standard Errors are clustered by OEM

**p < .05, **p < .01, ***p < .001 (two-tailed tests.).*

electric OEMs ($\beta = 1.161$, $p < 0.001$), reflecting the infrastructural complexity and integration needs of electric and connected vehicle development.

Model 2 shows that Net Logic has no significant effect on the formation of joint ventures ($\beta = 0.029$, $p > 0.1$), suggesting that joint ventures are not systematically associated with either displacement or dependency logic. However, they are significantly more likely when the partner is an auto supplier ($\beta = 1.904$, $p < 0.05$), and when the focal OEM is larger in size ($\beta = 1.810$, $p < 0.01$), consistent with the resource demands and governance complexity of this alliance form. Models 4 and 5 (Strategic Alliances and R&D Collaborations) show no significant relationship with Net Logic, implying that these alliance forms are relatively agnostic to the dominant competitive logic.

Models 2, 4, and 5 reveal that Net Logic has no significant association with the likelihood of forming joint ventures, strategic alliances, or R&D collaborations. This absence of effect suggests that these alliance forms are not strongly driven by the prevailing competitive logic, whether oriented toward displacement or dependence, but may instead reflect more enduring structural or organizational considerations. For instance, joint ventures are more likely when the partner is an auto supplier and when the OEM is relatively large, consistent with the resource intensity and managerial coordination required for this form. Meanwhile, R&D collaborations appear less common with tech startups and auto suppliers, possibly reflecting the limited absorptive capacity of startups and the hardware-focused capabilities of suppliers, which may make them less attractive for exploratory, knowledge-sharing partnerships. Taken together, these findings imply that while some alliance forms (e.g., acquisitions, technology partnerships) are responsive to shifts in competitive logic, others remain shaped more by partner characteristics and internal firm capabilities.

Table 4.10 Binary Logistic Regression predicting Redundant Alliances (2015-2024)

	Model 1 OEM Controls	Model 2 Control + Types	Model 3 Full	Model 4 Full + OEM FE
Net Logic			0.259***	0.264***
			(0.044)	(0.053)
Partner Types (Ref: OEM)				
Auto Supplier		-0.772	-1.011	-1.136
		(0.584)	(0.615)	(0.686)
Tech Startup		0.433	0.500	0.626
		(0.530)	(0.535)	(0.643)
Tech Giant		0.713	0.829	1.057
		(0.551)	(0.551)	(0.631)
Alliance Types (Ref: R&D)				
Acquisition/Investment		-0.440	-0.103	-0.202
		(0.333)	(0.324)	(0.343)
Joint Venture		1.142*	1.269*	1.415**
		(0.457)	(0.497)	(0.537)
Technology Partnership		0.648*	0.461	0.477
		(0.290)	(0.291)	(0.316)
Strategic Alliance		0.565*	0.641	0.658*
		(0.255)	(0.334)	(0.322)
R&D Spending (log)	-0.268	-0.246	-0.761	3.415
	(0.455)	(0.490)	(0.513)	(2.009)
Employee (log)	0.308	0.245	0.701	-1.998
	(0.395)	(0.423)	(0.410)	(1.861)
N of Alliances (t)	-0.065	-0.078	-0.027	-0.014
	(0.050)	(0.045)	(0.033)	(0.049)
Prior Alliances (3 years)	0.022	0.031	-0.044	-0.045
	(0.038)	(0.039)	(0.039)	(0.078)
Patents (log)	-0.002	0.012	-1.490***	-1.371***
	(0.232)	(0.232)	(0.400)	(0.407)
GDP Growth	-0.038	-0.018	0.043	0.015
	(0.053)	(0.054)	(0.053)	(0.057)
Industry Level Alliance	0.029***	0.030***	-0.013	-0.014
	(0.004)	(0.005)	(0.009)	(0.011)

Region (Ref: US)				
Europe	-0.100	-0.138	-0.418*	3.091*
	(0.178)	(0.218)	(0.212)	(1.465)
Asia	0.094	0.255	-0.048	1.384
	(0.172)	(0.195)	(0.281)	(0.932)
Electric OEM	-0.009	-0.278	-0.961**	0.366
	(0.276)	(0.311)	(0.343)	(2.652)
Constant	-1.387	-2.259	13.673**	-15.568
	(3.200)	(3.533)	(4.879)	(19.494)
OEM FE	No	No	No	Yes
N	517	517	517	517
R-Squared	0.059	0.112	0.175	0.206

Note: Dependent variable indicates whether an alliance is functionally redundant with a prior alliance by the same OEM. Net Logic tests Hypothesis 6. Model 4 includes OEM fixed effects. Standard Errors are clustered by OEM **p < .05, **p < .01, ***p < .001 (two-tailed tests.).*

Redundant Alliance Analysis

Table 4.10 presents logistic regression models predicting whether an alliance formed by an OEM is functionally redundant, defined as overlapping in purpose with a prior alliance within the past three years. The models test whether increasing infrastructural dependence, captured by higher values of Net Logic, is associated with a higher likelihood of forming such overlapping alliances, as predicted by Hypothesis 6. Model 4 includes OEM fixed effects to account for time-invariant unobserved firm-level heterogeneity.

Consistent with H6, the results show that Net Logic is positively and significantly associated with the likelihood of forming a redundant alliance across both the full model (Model 3: $\beta = 0.259$, $p < 0.001$) and the fixed-effects specification (Model 4: $\beta = 0.264$, $p < 0.001$). These findings suggest that OEMs are more likely to duplicate alliance functions under conditions of infrastructural dependence, supporting the argument that firms hedge against over-

reliance on dominant tech providers by engaging in multiple alliances in the same functional domain.

Alliance structure also plays a significant role in predicting redundancy. Joint ventures are positively and significantly associated with redundancy in both Model 3 ($\beta = 1.269$, $p < 0.1$) and Model 4 ($\beta = 1.415$, $p < 0.05$), suggesting that deep, equity-based collaborations are more likely to overlap functionally with prior partnerships. This may reflect the strategic weight and long-term commitment involved in joint ventures, which often replicate existing capabilities to scale efforts or benchmark partner performance. Strategic alliances are also positively associated with redundancy (Model 4: $\beta = 0.658$, $p < 0.1$), although the relationship is weaker and less consistent across models. This pattern aligns with the view that flexible, non-equity collaborations may be layered on top of one another to manage strategic uncertainty or diversify access within an evolving platform ecosystem. The partner type variables are not statistically significant, suggesting that redundancy is more closely tied to the logic of alliance form and the structure of competition than to the identity of the partner (e.g., tech startup vs. tech giant). The results offer robust support for Hypothesis 6: OEMs respond to increasing infrastructural dependence by forming functionally redundant alliances, a pattern consistent with a portfolio-based hedging strategy aimed at minimizing lock-in and preserving strategic autonomy under platform dependence.

4.6. Discussion

This study shows that the evolving nature of inter-industry competition between the automotive and technology industries shaped alliance behaviors in the autonomous vehicle domain. Focusing on OEMs, the statistical analysis reveals distinct patterns in partner selection, alliance type, and strategic intent across two competitive phases. Under strong displacement

logic, OEMs faced an existential threat from tech challengers and favored equity-based alliances, particularly acquisitions and investments with tech startups offering critical AI capabilities. These alliances were aimed at securing control, deep integration, and long-term relevance. The likelihood of forming such alliances was further amplified for OEMs with stronger internal R&D capabilities, which enhanced their absorptive capacity and ability to integrate external innovation. In contrast, under strong dependency logic, alliance behavior shifted markedly: technology partnerships increased as OEMs sought access to critical infrastructure while avoiding overreliance on dominant platform providers. Redundant alliances also became more prevalent during this phase, reflecting a strategy of diversification and flexibility in response to potential lock-in. While partner selection remained relatively stable, alliance forms shifted significantly across phases, indicating that inter-industry dynamics shaped how more than with whom OEMs partnered, although R&D capability still influenced partner choice.

These findings underscore that alliance strategies are not just driven by firm-level resource needs or environmental uncertainty but are deeply structured by the logic of inter-industry rivalry. Displacement logic encouraged OEMs to internalize emerging technologies and assert control over the direction of innovation, while dependency logic led to more modular and diversified collaborations aimed at managing asymmetrical power relationships. The form of competition evolved over time, but its role as a background force remained central, guiding how firms navigated partner selection, alliance design, and long-term positioning in a contested field. Inter-industry competition, in this sense, operates not just as a market condition but as a structuring context that reshapes the meaning and purpose of collaboration itself.

Implications

This study advances alliance theory by introducing and empirically substantiating a framework in which evolving inter-industry competitive logics structure alliance behavior during industry convergence. While existing research often attributes alliance formation to resource gaps, uncertainty, or learning opportunities, this paper shows that these drivers are shaped and conditioned by the nature of competitive pressure coming from a converging industry. In particular, the analysis reveals that competitive logic exerts greater influence on how firms partner (e.g., alliance form, governance structure, strategic intent) than on whom they partner with. As tech firms became consistently important actors across both phases, it was not their presence but their strategic positioning and how OEMs interpreted that positioning that determined the contours of alliance behavior. This finding contributes a more dynamic and structurally embedded account of alliance formation to the strategic management literature.

Second, the paper deepens our understanding of inter-industry competition by conceptualizing it as a multi-phase process rather than a binary conflict between distinct sectors. Displacement and dependence are not competing interpretations but sequential phases in a longer process of convergence. This conceptualization moves beyond static views of industry rivalry and toward a temporal model of evolving logics, in which the basis of competition shifts requiring firms to adopt different modes of strategic response. This also bridges macro-level transformations with firm-level strategic adaptation, demonstrating how field-level power dynamics manifest in concrete organizational decisions about alliance formation.

Finally, the findings speak to and extend ecosystem and field theories by highlighting how firms respond to shifting "rules of the game" in a transforming technological landscape. OEMs do not merely react to the structural power of tech platforms, they actively use alliance strategies to shape their position within an emerging ecosystem whose architecture is still fluid.

The rise of technology partnerships and redundancy strategies can be understood as field-contesting behaviors aimed at preserving autonomy in a space increasingly orchestrated by tech incumbents. In this way, the framework developed here contributes to a more agentic view of ecosystem participation and field navigation, where alliance behavior becomes a key instrument for negotiating institutional change.

Limitations

This study, while offering new insight into how evolving inter-industry competition structures alliance behavior, faces several limitations that also suggest productive avenues for future research. First, the use of patent-based measures to construct the Net Logic variable provides a systematic way to capture shifts in technological emphasis but offers only a partial view of how firms perceive displacement and dependence. These logics are ultimately interpretive constructs shaped by managerial sensemaking. Future work could complement this approach with textual analyses of corporate disclosures, executive interviews, or survey-based data to better capture firms' subjective interpretations of competitive threat and interdependence.

Second, while the focus on 20 leading OEMs ensures relevance to key strategic actors in the AV sector, the findings may not generalize to smaller OEMs or firms operating in different convergence contexts. Smaller firms may face different constraints or pursue alternative alliance strategies due to limited absorptive capacity or greater flexibility. Expanding the analysis to include a broader range of firm sizes, geographic regions, or stages of industry maturity could help test the portability of the displacement-dependence framework beyond the AV sector.

Third, although the modeling strategy controls for several relevant factors and clusters standard errors at the industry-year level, unobserved firm-level heterogeneity remains a potential limitation. The decision not to include firm fixed effects, due to the theoretical focus on

industry-level logics, leaves room for future studies to explore firm-specific reactions to inter-industry pressures using panel data models or mixed-method designs. If measures of perceived competitive logic at the firm level can be developed, more granular within-firm analysis would become possible.

Fourth, some alliance classifications, particularly those related to "redundant" or "technology" partnerships, are based on codified interpretations of strategic intent. Although these codings followed systematic criteria, they are ultimately inferred from observable patterns. Future studies could refine these classifications by drawing on internal firm data, surveys, or case-based interviews that directly probe alliance motivations and decision-making processes.

Future Work

This study focused on the alliance strategies of OEMs to theorize how evolving inter-industry competition logics shape firm behavior during industry convergence. However, future research could expand this framework in several directions to offer a more comprehensive account of alliance dynamics in contested fields.

First, a fuller analysis of the alliance network would require examining not only OEMs but also alliances among tech firms themselves. Preliminary observations suggest that tech–tech alliances (e.g., between cloud, chip, and software firms) often reflect merging or coalescing logics of infrastructure consolidation. These alliances may play a formative role in shaping the emerging architecture of mobility and thus deserve systematic attention. A future study could integrate OEM–tech, tech–tech, and even startup–startup ties to map the evolving topology of inter-organizational collaboration more completely.

Second, auto suppliers represent an underexplored but strategically significant actor. Their role in the AV space has evolved from component delivery to becoming innovation

partners and even platform providers in some cases. Tracking how suppliers reposition themselves in response to changing power dynamics between OEMs and tech firms would provide insight into identity transformation and capability renewal among legacy actors. Their alliances may be shaped less by disruption than by the need to stay essential in a reconfigured value chain.

Third, cross-national comparisons could enrich our understanding of how institutional context conditions alliance behavior under inter-industry competition. Countries differ widely in their antitrust regimes, industrial policy frameworks, and tolerance for platform power. A comparative study across markets such as the U.S., Germany, China, and Japan could reveal how local regulatory and policy environments mediate the intensity and direction of displacement and dependence dynamics.

Finally, the displacement–dependency framework proposed here could be extended to other domains of convergence, such as fintech, medtech, or edtech. Applying this lens to other sectors where incumbent industries face technologically sophisticated entrants could test the portability of the framework and generate broader insights about strategic behavior under convergence-driven rivalry.

Chapter 5 Conclusion

5.1 Summary

This dissertation has argued that competition is a central social mechanism shaping institutional change in the context of technological advancement. While often treated as a background market force, competition in fact organizes behavior across multiple social domains: industry, regulation, and discourse. Using the case of autonomous vehicles (AVs), a technology that spans diverse sectors, actors, and governance challenges, I examined how different forms of competition emerge and evolve, and how they structure institutional responses in distinct but interrelated arenas.

Chapter 2 examined how interstate competition shapes the diffusion of autonomous vehicle (AV) policy across U.S. states, both in terms of policy adoption and content. Using a novel network-based measure of competition derived from Census Job Flow data, I find that both structural equivalence and direct economic competition significantly increase the likelihood of policy adoption. However, their effects on policy content differ as structural equivalence leads to policy convergence, while the influence of direct competition is moderated by state capacity. Specifically, states with greater academic expertise are more likely to diverge in regulatory content when facing direct competition. This chapter shows that competitive pressures shape both the timing and design of policy and underscores the value of accurately measuring competition between states.

Chapter 3 turned to the discursive field and examined how policy adoption reshapes public framings of emerging technologies. I argued that policy is not only a regulatory instrument but also a symbolic act that affects how technologies are interpreted in public discourse. Importantly, I found that these framing effects are contingent on the level of competitive pressure a state faces. In highly competitive environments, policy adoption tends to amplify economic and technological narratives while sidelining ethical and social concerns. This suggests that competition influences not only what policies are enacted, but also how technologies are publicly legitimized.

Chapter 4 focused on alliance strategies between firms as the auto and tech industries increasingly intersect. I showed that inter-industry competition serves as a structuring force that shapes how firms navigate disruption. In the early stages, alliances were shaped by a displacement logic where automakers sought deep, equity-based partnerships to fend off disruption. Over time, however, a dependency logic emerged, as firms recalibrated strategies to reduce over-reliance on dominant tech providers. These shifts illustrate how competition drives firms to reconfigure not only their partnerships but also their long-term strategic orientations. Taken together, the findings across these chapters demonstrate that when technological change expands the resource space and unsettles existing institutional arrangements, competition becomes not a passive background variable but an active, generative force. It shapes who leads, who follows, and how the future is imagined across regulatory, industrial, and symbolic domains. In the sections that follow, I elaborate on the theoretical, methodological, and policy implications of this reconceptualization of competition, as well as its limitations and directions for future research.

5.2. Theoretical Contributions

This dissertation makes several theoretical contributions by placing competition at the center of sociological explanation. First, this dissertation shows that competition is a central mechanism through which institutional change unfolds during periods of technological disruption. When existing structures are unsettled by emerging technologies, competition becomes more than a background economic force, but it acts as a dynamic and relational process through which actors assess threats, reposition themselves, and redefine the boundaries of their fields. I demonstrate that competition is not uniform or singular but takes multiple forms, such as inter-industry rivalry, interstate policy competition, and symbolic struggles over meaning, and involves a wide range of actors including firms, governments, and media. These different forms of competition operate simultaneously and interactively, shaping not only when actors move but also how they justify and frame their actions.

Second, this dissertation contributes a dynamic theory of competition by tracing its evolution across time and institutional domains. Rather than treating competition as static or singular, I show how it unfolds in phases, shifts in logic, and reconfigures the terms of action. In the industrial field, I identify a transition from a displacement logic, where tech firms threatened to replace OEMs, to a dependency logic, where OEMs manage infrastructural reliance on powerful platform providers. This conceptualization of evolving competition aligns with field theory's emphasis on strategic interaction but adds a temporal dimension: competition is not just a feature of fields, but a force that transforms their structure and rules over time. This insight helps explain why actors shift strategies even when their formal positions remain constant.

Third, this dissertation contributes to science and technology studies (STS) by bridging disciplinary silos and offering a sociological account of how technologies and social structures

co-evolve. While STS has richly described how technologies are socially constructed and politically negotiated, it has often foregrounded interpretive flexibility and stabilization over strategic rivalry (Bijker, Hughes, and Pinch 1987; Jasanoff 2005). By introducing competition as a structuring logic into this conversation, I show how the development and governance of emerging technologies are shaped not only by meaning-making processes, but also by rivalry over jurisdiction, visibility, and symbolic control. AVs are not just innovations to be regulated but they are contested terrains through which actors seek to shape the future of mobility, labor, and infrastructure.

In sum, this dissertation theorizes competition as a generative and evolving force that operates across domains and conditions how technological change is absorbed, resisted, and narrated. It invites sociologists to re-engage with competition not as a taken-for-granted economic principle, but as a deeply social and political mechanism that reshapes institutions in moments of disruption.

5.3 Methodological Contributions

This dissertation offers several methodological innovations for studying how competition operates across institutional domains. Understanding competition as a structuring logic requires methodological approaches capable of capturing relational dynamics, field positioning, and interpretive shifts across time and context.

First, this dissertation advances new techniques for measuring competition in both industrial and policy contexts. In the industrial domain, I analyze competition between firms from different sectors by linking alliance behavior to firm-level technological specialization. Drawing on patent classification data, I operationalize inter-industry distance through firms' positions within a shared technology space. This approach allows me to move beyond

assumptions of sectoral identity (e.g., “auto” vs. “tech”) and instead model how firms relate to one another based on technological capabilities and innovation trajectories. It provides a more granular, dynamic, and behaviorally grounded measure of competition than is typically available in studies of alliance formation or industry convergence. In doing so, it opens new pathways for analyzing how competition unfolds not only between firms, but between evolving technological domains.

In the policy domain, I move away from traditional spatial proximity measures of competition and instead develop a network-based measure of competition between U.S. states. Using Census Job Flow data, I construct networks of labor mobility that capture the flow of skilled workers between states over time. This allows me to model how states monitor and respond to one another as competitors in a shared economic field, particularly within the context of the knowledge economy. Unlike geographic contiguity or partisan similarity, this measure reflects how states are socially and economically linked through talent migration and industry structure, thus better capturing the field dynamics of policy diffusion under competitive pressure. This approach offers a more relational, sociologically grounded alternative to standard models of competitive federalism and innovation policy adoption.

Second, this dissertation introduces a novel approach to measuring discursive framing in media coverage of emerging technologies. In Chapter 3, I use Sentence-BERT (SBERT), a state-of-the-art transformer-based model, to classify AV-related news articles into economic, technological, and ethical frames. SBERT enables semantic similarity comparisons between full sentences and concept-level embeddings, allowing for high-resolution, context-aware classification across a large, noisy corpus of over 13,000 local news articles. This method advances frame analysis beyond keyword matching or topic modeling by incorporating sentence-

level meaning and contextual nuance. In doing so, it provides a more accurate account of how public discourse around AVs is shaped by policy adoption and conditioned by competitive environments.

Together, these methodological choices reflect a broader contribution to sociological research: demonstrating how relational, computational, and interpretive methods can be combined to operationalize abstract social mechanisms like competition. Rather than treating competition as a fixed input or a binary condition, I model it as a dynamic field relationship, one that varies across time, space, and institutional context. This approach is particularly useful for studying emerging technologies, where traditional boundaries are unstable, field positions are in flux, and symbolic struggles play a central role in shaping outcomes.

5.4 Limitations and Directions for Future Work

This dissertation has several limitations that open important avenues for future research. First, the study is limited by its focus on the U.S. context, which may not reflect how competition operates in other political and institutional settings. A range of theoretical traditions, including innovation systems theory, business systems theory, and varieties of capitalism, emphasize the diversity of institutional arrangements across countries (Hall and Soskice 2001; Whitley 1999). Exploring how competition is organized and governed in different national contexts would help refine our understanding of how political economies shape the dynamics of emerging technology governance.

Second, the empirical focus on autonomous vehicles (AVs) provides a rich but bounded case. While AVs are a highly visible and capital-intensive technological field, they represent only one segment of the broader landscape of emerging technologies. Other domains, such as generative AI, large language models (LLMs), and synthetic biology, may exhibit different

innovation logics, regulatory challenges, and forms of inter-organizational rivalry. Comparative studies across these domains would allow researchers to examine how sector-specific features shape the expression and consequences of competition.

Third, this dissertation focused on competition within individual domains: industry, regulation, and discourse. It did not fully explore how competitive dynamics unfold across these domains in interaction. In practice, actors often engage simultaneously in multiple fields: firms pursue market advantage while shaping public narratives, and states compete for firms while also signaling leadership through regulation. Future research could investigate how layered forms of competition, such as between firms and between states, interact to shape outcomes like policy design or alliance formation. Understanding these cross-domain dynamics would contribute to a more integrated theory of competition under conditions of technological disruption.

Fourth, the dissertation relies primarily on macro-level data sources, including alliance records, labor mobility flows, and computationally coded media texts. While effective for tracing quantitative patterns, these approaches cannot fully capture how actors interpret or experience competition in context. Future studies could enrich these findings by incorporating qualitative methods such as interviews, ethnographies, or interpretive discourse analysis (Lamont and` Swidler 2014). Such work would shed light on the symbolic, affective, and embodied dimensions of competition.

Finally, this dissertation focused primarily on the processes and conditions under which competition emerges and unfolds, rather than its long-term consequences. A key direction for future research is to examine what competition produces. Does it lead to sustained innovation, deeper inequality, institutional fragmentation, or more adaptive governance? Addressing these

questions would clarify not only how actors compete, but what kinds of futures competition helps bring into being.

Appendix

Appendix Table A.1 Examples of classification of AV related Paragraphs using SBERT similarity scores

Paragraphs	Similarity Score	Threshold
“We've grown together,” Shapiro said. But as much as Shapiro loves bringing the convention to the warm familiarity of Las Vegas, the future of the trade show in Southern Nevada became cloudy for a time last year.	0.119	Fail
“Las Vegas has done a phenomenal job with everything,” Shapiro said. And the community has benefited from CES' growth as well, said Chris Meyer, vice president of global business sales for the Las Vegas Convention and Visitors Authority.	0.165	Fail
The Model S starts at $68,000 and goes up to $134,000, depending on power and speed. The Tesla Model X, its sport-utility vehicle, begins at $85,000. Its midmarket entry, the long-awaited Tesla Model 3, is expected to hit showrooms in the second half of the year and is priced around $35,000.	0.248	Fail
Jack Landskroner, a lawyer for Brown's family, said Thursday the family plans to evaluate all of the information from government agencies investigating the crash “before making any decisions or taking any position on these matters.” Tesla introduced restrictions on Autopilot after concerns arose that the system lulled users into a false sense of security through its “hands-off” driving capability.	0.463	Pass
Brown's death raised questions about whether regulators have the authority to oversee rapidly developing vehicle technologies. Videos posted by Tesla drivers on YouTube showed close calls on the road with Autopilot.	0.515	Pass
Connectivity in rural areas will also provide additional testing grounds for emerging technologies, like autonomous vehicles and drones. “Camera images, roadway sensors and weather monitoring data will be able to freely flow to and from users in rural settings to assist with transportation issues related to traffic incidents, infrastructure condition, special event management, weather hazards, and security issues,” said Tina Quigley, general manager of the Regional Transportation Commission.	0.533	Pass

Appendix Table A.2 Summary of Local Newspaper Corpus and Data Filtered by State

State	Journal	N of Articles	N of Pargarpahs	N of AV related Paragraphs
Alabama	Birmingham News	71	696	282
Arizona	Arizona Republic	622	7,022	2,813
Arkansas	Arkansas Democrat-Gazette	259	3,341	860
California	Los Angeles Times	898	6,068	2,608
Colorado	Denver Post	249	2,416	846
Connecticut	Hartford Courant	160	1,917	640
Delaware	The News Journal	274	2,416	991
Florida	Tampa Bay Times	230	2,796	582
Georgia	Atlanta Journal-Constitution	324	3,761	1,163
Hawaii	Honolulu Star-Advertiser	105	1,085	225
Idaho	Idaho Falls Post Register	27	268	94
Illinois	Chicago Tribune	570	6,762	2,582
Indiana	Indianapolis Star	239	2,487	799
Iowa	Des Moines Register	277	2,621	907
Kansas	Wichita Eagle	35	407	74
Kentucky	Courier - Journal	231	1,825	808
Louisiana	New Orleans Advocate	44	685	71
Maine	Portland Press Herald	198	998	317
Maryland	Baltimore Sun	115	1,340	447
Massachusetts	Boston Globe	638	9,229	2,915
Michigan	Detroit Free Press	1,381	18,672	7,587
Minnesota	Star Tribune	164	2,440	656
Mississippi	Clarion Ledger	256	1,974	866
Missouri	St. Louis Post-Dispatch	181	2,003	514
Montana	Billings Gazette	80	688	185
Nebraska	Omaha World-Herald	95	1,241	233
Nevada	Las Vegas Review-Journal	248	2,767	945
New Hampshire	Union Leader	93	886	334
New Jersey	Courier Post	237	1,912	827
New Mexico	Albuquerque Journal	268	2,465	957
New Mexico	Las Cruces Sun	268	2,465	957
New York	The Journal News	223	1,974	797
North Carolina	News & Observer	80	959	274
North Dakota	Bismarck Tribune	190	1,765	709
Ohio	Dayton Daily News	486	4,992	1,674
Oklahoma	Oklahoman	64	617	177

Oregon	Oregonian	128	1,241	295
Pennsylvania	Pittsburgh Post	869	10,254	3,330
Rhode Island	Providence Journal	202	2,679	850
South Carolina	Post and Courier	211	2,602	604
South Dakota	Argus Leader	264	2,196	901
Tennessee	Tennessean	233	2,572	873
Texas	Houston Chronicle	365	3,892	986
Utah	Deseret News	126	1,545	628
Vermont	Burlington Free Press	169	1,347	593
Virginia	Daily Press	177	1,896	636
Washington	Seattle Times	297	3,825	1,297
West Virginia	Charleston Gazette	114	1,164	437
Wisconsin	Milwaukee Journal Sentinel	82	1,112	305
Wyoming	Wyoming Tribune-Eagle	30	324	97
Total		13,147	142,609	49,548

Appendix Table A.3 Illustrative Examples of Frame Classifications using SBERT similarity score

Frames	Paragraphs	Similarity Score
Economic Frame	Trucking, automation and the future of work in the United States WASHINGTON The future of trucking may tell us a lot about the future of work. It's no secret many Americans fear losing their jobs to automation. In a Pew Research Center poll last October, nearly three-quarters of respondents worried that "computers and robots could do most of the work currently done by humans." Yet the job market seems to be sending the opposite message: With a low unemployment rate of 4.1 percent, many companies say they can't find good workers.	0.621
Technological Frame	We looked at the top technologies, which are becoming more available, not just in high-end cars. It's important drivers learn about them and how they work - especially mature drivers. The question has been, how do we help older drivers stay on the road safely for as long as possible? We think these technologies are important.	0.632
Social/Ethical Frame	They also collide with those who believe such standards can be derived from popular consensus, such as the Moral Machine project at the Massachusetts Institute of Technology. Researchers there devised an online test in which people can grapple with ethical quandaries a self-driving car might face when a fatal accident is unavoidable. But ethical challenges in robotics go beyond self-driving cars. Should a companion robot report a child's confidences to parents, or more troublingly, to the manufacturer of the device? How should a self-driving wheelchair respond if its occupant tries to commit suicide by plunging down stairs?	0.733
Unframed	Plausible deniability is a common defense in corporate America against legal exposure, and it colors how technology companies operate. For example, when Uber acquired Otto, the self-driving car company founded by Anthony Levandowski, general counsel Salle Yoo ordered an outside report on Otto as part of the due diligence process.	0.273

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