Financial Structure, Intellectual Property Rights, and the Composition of Innovation

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Abstract

This thesis investigates how financial development and intellectual property rights jointly shape the composition of innovation. Motivated by the "patent puzzle" and utilizing cross-country panel data, I estimate two-way fixed effects models linking patent quality and intensity to distinct financing channels and IPR strength. Results show that equity market depth is positively associated with innovation quality. However, the marginal effect of stronger patent protection declines as markets deepen, becoming negative in highly developed systems, a pattern reinforced by supplementary models of breakthrough intensity. In contrast, bank-based and entrepreneurial finance exhibit weaker and less stable associations, primarily affecting patent intensity rather than quality. These findings suggest that financial structure and legal institutions determine not only the scale of innovative activity, but whether it drives frontier-expanding technological progress as well.

1 Introduction

For adherents of endogenous growth theory, long-run prosperity is propelled by technologies that alter production, reshape markets, and expand what societies can achieve [Romer, 1990, Aghion and Howitt, 1992]. From the combustion engine and the printing press to the CPU and contemporary large language models, technological progress has repeatedly driven sustained economic growth. Endogenous growth theory formalized this intuition by placing innovation at the center of the growth process. Yet we still understand far less about the conditions that give rise to genuinely transformative innovations, rather than incremental, or low value additions to the technological frontier

A central challenge is measurement. Traditional proxies for innovation such as patent counts or R&D expenditure perform poorly in capturing economically meaningful technological progress. The "patent puzzle" illustrates this tension: global patenting and R&D spending have risen substantially, yet productivity growth in many advanced economies has stagnated [Boldrin and Levine, 2013]. This disconnect suggests that the quantity of innovation tells us little about its economic significance. A more informative measure lies in innovation quality, understood as the technological and economic value embedded in inventive output. A growing literature develops patent-level indicators to capture this dimension, drawing on patent-level micro data to infer quality from the structure of citation networks and disclosure characteristics [Squicciarini et al., 2013, Trajtenberg et al., 1997, Lanjouw and Schankerman, 2004, Hall et al., 2005, Kogan et al., 2017]. While no single indicator is definitive, as each captures a distinct facet of quality, composite measures combining these dimensions provide a more robust proxy for meaningful innovation than raw patent counts or R&D expenditure

Once innovation quality can be measured and compared across countries and over time, we can ask a deeper question: under what institutional and financial environments do high-quality innovations arise, and when do economies instead produce more patents, but not better ones? A revolutionary technology begins as an idea in a human mind, but its realization depends on a complicated ecosystem of incentives, financing, and legal institutions. On the financing side, firms require external capital to transform ideas into marketable technologies. Banks, public equity markets, and venture capital each provide distinct screening mechanisms, risk tolerances, and monitoring structures. Relationship lending can enable firms to leverage intellectual property as collateral [Mann, 2018], yet banks may end up financing patent portfolios optimized for borrowing rather than innovations with real technological value. Public equity markets can aggregate dispersed information and reward high-growth firms [Fama, 1970], but they may also respond to scale, momentum, or hype rather than underlying technological quality. Venture capital, with its high risk tolerance and active governance, may identify frontier innovators, but high-profile failures highlight its limits.

Legal institutions shape incentives alongside financial structure. Strong intellectual property rights (IPR) grant temporary monopoly profits in exchange for disclosure, but they also generate tradeoffs between patenting and secrecy [Klein, 2020]. When protection is strong, firms may choose patenting over secrecy, increasing disclosure and potential spillovers. When protection is weak, firms may rely more heavily on secrecy, limiting diffusion. Stronger formal protection does not necessarily imply socially optimal innovation. Patents can facilitate productive disclosure, but they can also support strategic fencing, defensive accumulation, or rent-seeking behavior. The net effect of IPR on innovation quality may therefore depend on the broader financial environment.

Recent theoretical work emphasizes precisely this interaction. In a Schumpeterian framework with financial frictions, Klein and Yang [2025] show that the growth effects of patent protection depend on financial development: when financial markets are shallow and frictions severe, stronger patent rights can stimulate growth by easing financing constraints; when markets are deep, the marginal growth benefits of stronger protection diminish. Similarly, Maskus et al. [2019] provide empirical evidence that patent protection stimulates R&D primarily in financially underdeveloped economies, suggesting that strong IPR can partially substitute for weak financial systems. However, much of the existing cross-country evidence evaluates innovation using qualitative measures, with the composition of innovation across the quality distribution remaining less explored.

This thesis seeks to contribute to a wider understanding of how economies can foster the kinds of transformative technologies that drive long-run growth. Using OECD Patent Quality Indicators and cross-country panel data, I estimate two-way fixed effects models linking patent quantity and patent quality to distinct financing channels, IPR strength, and their interaction. The central empirical result concerns equity market development. Deeper equity markets are positively associated with higher patent quality. At the same time, the marginal effect of stronger patent rights on quality declines as market depth increases. This interaction remains statistically robust across specifications and survives incremental inclusion of controls. In financially shallower systems, stronger IPR is associated with improvements in patent quality. In financially deeper systems, the same strengthening of patent protection yields smaller, and in some specifications negative, effects on quality. By contrast, bank-based financial development exhibits weaker and less stable relationships with quality and is more consistently associated with patent quantity rather than quality.

These findings support a compositional interpretation of innovation. Financial systems and patent regimes jointly influence whether inventive activity concentrates in higher-quality, productivity-enhancing innovation or expands primarily along the extensive margin through lower-value patent proliferation. To further examine frontier innovation, I estimate zero-inflated negative binomial models of breakthrough patents (top 1% quality). The distribution of breakthrough counts exhibits substantial overdispersion and excess zeros, motivating a framework that distinguishes between structural non-participation in frontier innovation and the intensity of breakthrough production conditional on participation. These supplementary models reinforce the view that financial and legal regimes shape not only the volume of innovation, but its allocation across the quality spectrum.

The rest of the analysis proceeds as follows. Section 2 reviews the theoretical and empirical literature on innovation, financial development, and intellectual property rights. Section 3 outlines the empirical framework, including the two-way fixed effects baseline and the zero-inflated negative binomial model for breakthrough innovation. Section 4 describes the data and key variables. Section 5 presents the main results, beginning with average patent quality and quantity before turning to frontier innovation. Section 6 concludes with [something... I'm yet to actually write this].

2 Literature Review

2.1 Innovation and Endogenous Growth

Endogenous growth theory places innovation at the core of long-run economic development. In the canonical models of Romer [1990] and Aghion and Howitt [1992], technological progress arises from intentional R&D investment and creative destruction. Firms innovate to obtain temporary monopoly profits, and the pace of innovation determines sustained productivity growth. These frameworks emphasize that incentives, market structure, and institutional environments shape innovative effort.

However, these models typically treat innovation as homogeneous. In practice, innovations differ widely in technological significance and economic value. Some inventions fundamentally shift production frontiers, while others represent incremental improvements or strategic extensions of existing technologies. The distinction between high-quality, frontier-expanding innovation and lower-value or defensive patenting becomes especially important in light of the patent puzzle: patenting and R&D expenditure have increased substantially, yet productivity growth has not followed proportionally [Boldrin and Levine, 2013]. Understanding growth therefore requires not only measuring the volume of innovation, but examining its composition.

2.2 Measuring Innovation Quality

Because innovation quality is not easily observable, researchers rely on patent-based indicators to approximate technological and economic value. Forward citations capture the extent to which subsequent inventions build upon a given patent, serving as a proxy for technological influence [Hall et al., 2005, Trajtenberg et al., 1997]. Patent family size and the number of claims reflect the private value that firms attribute to their inventions [Lanjouw and Schankerman, 2004]. Measures of originality and generality capture technological breadth and cross-field impact, while citations to non-patent literature indicate scientific relevance [Squicciarini et al., 2013].

Building on Lanjouw and Schankerman [2004], Squicciarini et al. [2013] propose composite indices, that, when aggregated allow cross country and inter temporal comparison. Compared to raw quantity measures, these composite indicators provide a richer representation of whether innovative activity reflects frontier technological progress or incremental patent accumulation.

2.3 Finance and Innovation

A substantial literature examines how financial development affects innovation and growth. Financial intermediaries and markets alleviate credit constraints, mobilize savings, and allocate capital toward productive investment [Levine, 2005]. Because R&D is risky, intangible, and difficult to collateralize, innovative firms may be especially sensitive to financing conditions [Hall and Lerner, 2010].

Different financing channels provide distinct forms of support. Relationship-based bank lending can reduce information asymmetries and enable firms to leverage intangible assets such as patents as collateral [Mann, 2018]. Public equity markets may facilitate risk-sharing and price discovery, potentially rewarding high-growth and high-risk projects [Hall et al., 2005]. Venture capital combines funding with active governance and screening, often targeting early-stage, high-growth firms [Lerner and Nanda, 2020].

At the same time, financial development may alter the type of innovation pursued. Bank-based systems may favor safer, incremental innovation consistent with stable repayment. Equity markets, while potentially supportive of high-growth firms, may also respond to speculative dynamics or short-term performance pressures. These institutional differences suggest that financial structure may shape not only the quantity of innovation, but its allocation across the quality distribution.

2.4 Intellectual Property Rights and Financial Development

Intellectual property rights influence innovation incentives by granting temporary monopoly protection in exchange for disclosure. Stronger patent protection can increase expected returns to innovation, but may also generate distortions through strategic patenting, rent-seeking, or reduced competition. Cross-country variation in IPR strength has therefore become central to empirical analysis.

The Park Index provides a standardized measure of statutory patent protection across countries, capturing dimensions such as coverage, enforcement, and duration [Park, 2008]. Empirical evidence on the relationship between IPR and innovation, however, remains mixed. Stronger patent protection may stimulate R&D in some contexts while yielding limited or even negative welfare effects in others.

Recent work emphasizes the interaction between patent protection and financial development. In a Schumpeterian model with financial frictions, Klein and Yang [2025] demonstrate that the growth effects of stronger patent protection depend critically on financial depth. When financial markets are underdeveloped and frictions severe, stronger IPR can ease financing constraints and stimulate growth. As financial markets deepen and frictions decline, the marginal growth benefits of stronger patent protection diminish.

Similarly, Maskus et al. [2019] provide empirical evidence that patent protection increases R&D investment primarily in countries with relatively low levels of financial development. Their results suggest that strong IPR can partially compensate for weak financial systems by enhancing firms' ability to secure external finance. In financially advanced economies, by contrast, the incremental impact of stronger patent protection appears smaller.

Despite this progress, most cross-country studies focus on aggregate patent counts, R&D spending, or growth outcomes. Much less attention has been paid to how financial structure and IPR regimes jointly shape the quality of innovation. If stronger patent protection in financially developed systems primarily encourages incremental or defensive patenting, aggregate increases in patenting may mask shifts toward lower-value innovation. Conversely, in financially constrained environments, stronger IPR may facilitate access to capital for more transformative projects.

3 Empirical Framework

3.1 Motivation and Overview

This section outlines the empirical strategy used to examine how financial structure and intellectual property institutions jointly shape innovative outcomes. The central objective is to distinguish between the volume of innovation and its composition, particularly with respect to patent quality and breakthrough activity.

Innovation is inherently multi-dimensional. Aggregate patent counts conflate incremental and frontier innovation, while average quality measures can obscure the skewed distribution of technological importance. A small fraction of patents accounts for a disproportionate share of long-run technological progress, yet most country-year observations record no breakthrough innovations at all. Empirically capturing this distributional structure requires moving beyond linear specifications.

The analysis proceeds in two stages. First, I estimate two-way fixed effects (TWFE) panel regressions relating financial development, intellectual property protection, and their interaction to measures of average patent quality and patent quantity. These models exploit within-country variation over time while controlling for unobserved time-invariant heterogeneity and global shocks. They establish the baseline relationships and reveal systematic differences across financial channels.

Second, because frontier innovation is rare and highly concentrated, I explicitly model breakthrough activity using zero-inflated negative binomial (ZINB) models [UCLA Statistical Consulting Group, n.d.]. This framework distinguishes between (i) the probability that a country is structurally unlikely to produce frontier innovation and (ii) the intensity of breakthrough production conditional on participation. Together, these approaches allow the analysis to address the central question of the thesis: Do financial structure and patent institutions shape not only how much innovation occurs, but whether it reflects high-quality, frontier-expanding technological progress?

3.2 Baseline Two-Way Fixed Effects Model

The baseline specification estimates the relationship between financial development, intellectual property rights, and innovation outcomes using a two-way fixed effects panel model:

$$Y_{it} = \beta_0 + \beta_1 FD_{it} + \beta_2 IPR^c_{it} + \beta_3 (FD_{it} \times IPR^c_{it}) + \mathbf{X}'_{it}\beta + \alpha_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where Y_{it} denotes either: Average patent quality (OECD composite index), or Log patents per 1,000 researchers. FD_{it} measures financial development and is alternately defined as: Log stock market capitalization to GDP (market-based finance), Log domestic bank credit to GDP (bank-based finance), or Log venture capital investment. IPR^c_{it} is the Park index of patent protection [Park, 2008]. $\mathbf{X}'_{it}$ includes controls for income per capita, trade openness, R&D intensity, and tertiary education attainment. Country fixed effects α_i absorb time-invariant characteristics. Year fixed effects λ_t capture global shocks. Standard errors are clustered at the country level.

The coefficient of primary interest is β_3, which captures how the marginal effect of patent protection varies with financial development. The marginal effect of IPR on innovation is:

$$\frac{\partial Y_{it}}{\partial IPR^c_{it}} = \beta_2 + \beta_3 FD_{it}$$

A negative β_3 implies that the impact of stronger patent protection declines as financial markets deepen. This interaction is central to the compositional interpretation developed in the Results section.

The TWFE specification isolates within-country changes over time. Consequently, the estimated relationships reflect how shifts in financial depth and IPR strength within a country are associated with changes in innovation outcomes, rather than cross-country level differences.

3.3 Modeling Frontier Innovation: Zero-Inflated Negative Binomial

Breakthrough innovation exhibits two defining features: extreme overdispersion and excess zeros (see Figure A.3). The variance of breakthrough counts substantially exceeds the mean, invalidating a Poisson assumption, and a large fraction of country-year observations record zero breakthroughs. These zeros likely reflect a mixture of structural incapacity and stochastic variation. The variance of a Negative Binomial distribution is defined as:

$$Var(Y_{it}) = \mu_{it} + \alpha\mu_{it}^2$$

where α represents the overdispersion parameter. As $\alpha \to 0$, the variance approaches the mean (μ_{it}) and the distribution converges back to the Poisson. Note that in the empirical estimation, the software package I use (R) parameterizes this by estimating θ, which is the inverse of the dispersion parameter ($\theta = \alpha^{-1}$). Therefore, the significance of $\ln(\theta)$ in the results tables confirms the presence of overdispersion and validates the Negative Binomial specification. For a full mathematical derivation of the zero-inflated likelihood function and probability mass functions, see Ulrich and Pohlmeier [1995].

Following a standard ZINB framework [UCLA Statistical Consulting Group, n.d., Long, 1997], the model is estimated in two parts. The selection margin models the log-odds of being a structural non-innovator, and the intensity margin models the expected breakthrough count μ_{it} via a log-link function, incorporating total patenting as an exposure offset.

3.4 Selection Equation

The zero-inflated component, which models the log-odds π_{it} of a country being a "structural non-innovator" in a given year, is specified using a logit link function:

$$\ln\left(\frac{\pi_{it}}{1-\pi_{it}}\right) = \gamma_0 + \gamma_1 \ln(\text{GDP per capita}_{it}) \tag{2}$$

where π_{it} denotes the probability that country i in year t is in the zero-generating state. Higher income levels are expected to reduce this probability, reflecting greater absorptive capacity and technological infrastructure. Negative coefficients in this equation indicate a lower likelihood of structural exclusion from frontier innovation.

3.5 Intensity (Breakthroughs per Patent)

Conditional on being capable of producing breakthroughs, the expected number of breakthrough patents μ_{it} follows a negative binomial process with a log link function:

$$\ln(\mu_{it}) = \beta_0 + \beta_1 FD_{it}^c + \beta_2 IPR_{it}^c + \beta_3(FD_{it}^c \times IPR_{it}^c) + \mathbf{X}_{it}'\beta + \ln(\text{Patents}_{it}) \tag{3}$$

where μ_{it} represents the expected count of breakthrough patents. The term $\ln(\text{Patents}_{it})$ enters as an offset, effectively modeling the rate of breakthrough production. This ensures that the model estimates breakthrough intensity relative to the total patenting volume rather than raw counts.

Because fixed effects are incompatible with zero-inflated models, these ZINB specifications are estimated without country and year fixed effects. They are therefore interpreted as supplementary robustness analyses rather than causal estimates.

4 Data

4.1 Patent Data and Innovation Measures

The core innovation measures in this thesis are derived from the OECD Patent Quality Indicators database [Squicciarini et al., 2013]. The dataset provides patent-level indicators derived from the EPO's PATSTAT, harmonized across countries and technology classes. This analysis uses the *Patent Quality Index 4*, an unweighted average of a patent's forward citations (5 years), Family Size, Claims, and Generality.

The primary dependent variable in the baseline analysis is average patent quality at the country-year level, constructed as the mean of the OECD composite quality index (scaled 0-100) across patents filed by inventors residing in a given country in year t. This measure captures the average technological significance of inventive output.

To contrast quality with scale, I also construct a measure of patent quantity, defined as patents per 1,000 researchers and expressed in logarithmic form. Normalizing by researchers mitigates size effects and better reflects innovative intensity rather than population scale.

In addition to average quality, I employ a measure of breakthrough innovation. Following the classification of Ahuja and Lampert [2001], breakthrough patents are defined as those in the top 1% of citation distribution within their technology class and application year. These are aggregated to the country-year level to obtain breakthrough counts. Because breakthrough activity is highly skewed and frequently zero, it is analyzed separately using zero-inflated negative binomial models.

4.2 Financial Development

Financial development is measured along three distinct channels to capture differences in institutional structure:

- Market-based finance: Log stock market capitalization to GDP [World Bank, 2025].
- Bank-based finance: Log domestic credit to the private sector as a share of GDP [World Bank, 2025].
- Venture capital: Log venture capital investment, measured in constant dollars [OECD, 2025].

These measures capture the relative depth and activity of equity markets, traditional banking systems, and risk-oriented entrepreneurial finance, respectively. Each channel is entered separately in baseline specifications to isolate its distinct association with innovation outcomes.

4.3 Intellectual Property Rights

Intellectual property protection is measured using the Park Index [Park, 2008], a widely used cross-country indicator of statutory patent protection strength. The index aggregates five dimensions of patent law, including coverage, duration, enforcement mechanisms, and international treaty membership. Higher values indicate stronger formal protection.

While the index captures legal design rather than enforcement outcomes or litigation intensity, it provides a consistent measure of cross-country variation in patent regimes over time. The Park Index is also mean-centered before interacting with financial variables, and interpolated via a 5-year fill.

4.4 Control Variables

To isolate the relationship between financial structure, IPR, and innovation, the baseline regressions include standard macroeconomic controls:

- Log GDP per capita (constant dollars), capturing income level and absorptive capacity.
- Trade openness (exports plus imports as a share of GDP), capturing exposure to global markets.
- Log R&D expenditure as a share of GDP, capturing innovative input intensity.
- Log tertiary education attainment, capturing human capital.

These variables are commonly used in cross-country innovation and growth regressions and account for factors that may jointly influence financial development and innovative performance. All control variables are sourced from The World Bank's WDI database [World Bank, 2025].

4.5 Descriptive Patterns

The data reveal several facts that motivate the empirical strategy. First, patent quality and patent quantity are only weakly correlated across country-years, suggesting that scale and value capture distinct dimensions of innovation (see Figure A.5). Second, breakthrough counts exhibit substantial overdispersion: the variance far exceeds the mean, and a large fraction of country-year observations record zero breakthroughs. These features justify modeling quality separately from quantity and motivate the use of ZINB specifications for frontier innovation. Descriptive statistics for all primary variables are provided in Table A.1 in the Appendix.

5 Results

5.1 Market-Based Finance and Patent Quality

Table 1 reports five specifications corresponding to equation (1). Column (1) holds all covariates constant, while Columns (2) through (5) incrementally add controls; country and year fixed effects are retained across all models. The discussion focuses primarily Columns (3) and (4), which balance sample size and controls.

Table 1: Market Finance and Patent Quality

	Dependent variable:				
	Patent Quality				
	(1)	(2)	(3)	(4)	(5)
Market Cap	0.390	0.364	0.390	0.975**	0.602
	(0.281)	(0.300)	(0.316)	(0.396)	(0.632)
IPR Strength	1.751*	2.036**	2.068**	4.285**	3.859***
	(0.907)	(0.937)	(0.952)	(1.946)	(1.214)
Market Cap × IPR	−0.651***	−0.676***	−0.685***	−1.168***	−1.053**
	(0.229)	(0.232)	(0.232)	(0.394)	(0.430)
GDP per Capita		−0.788	−0.837	−2.337*	−0.819
		(1.821)	(1.856)	(1.386)	(1.678)
Trade Openness			−0.443	−0.515	−1.299
			(1.273)	(1.834)	(1.900)
R&D Expenditure				−0.432	−1.372
				(1.615)	(2.344)
Tertiary Education					−1.244*
					(0.754)
Observations	1,431	1,422	1,422	880	636
R^2	0.020	0.023	0.023	0.025	0.015
Adjusted R^2	−0.048	−0.045	−0.046	−0.069	−0.121

Note: *p<0.1; **p<0.05; ***p<0.01
Country & Year FE included. Clustered SE in parentheses.
Within R^2 reported.

In Column (3), the coefficient on IPR strength (mean-centered Park Index) is positive and statistically significant, while the interaction between log market capitalization and IPR is negative and significant at the 1% level. Because IPR is centered, its coefficient represents the marginal effect of stronger patent protection evaluated at the sample mean level of financial depth. The estimated turning point is given by:

$$\widehat{FD}^* = -\frac{\beta_{IPR}}{\beta_{\text{Interaction}}}$$

Using Column (3) coefficients, the threshold occurs at approximately $\widehat{FD}^* = 3.02$ in log market capitalization. This value lies below the sample mean of financial depth, indicating that the marginal effect of stronger patent protection becomes negative within the observed range of the data.

Column (4), reinforces this pattern. The interaction term remains negative and highly significant ($\widehat{FD}^* = 3.66$), while the direct coefficient on market capitalization remains positive and gains significance. Evaluated at the sample mean, stronger IPR increases patent quality only in financially shallow systems. As market depth rises, the marginal effect declines and becomes negative for financially advanced economies. A joint Wald test in Column (4) rejects the null that financial depth and the interaction term are jointly zero (p = 0.0032), confirming that the relationship is not driven by isolated coefficient instability.

Figure 1 illustrates the interaction graphically, showing the declining marginal effect of IPR across increasing levels of financial development. The turning point reflects the estimates in Column (4), given the economies present in the sample [I should add cross-ref to sample countries in appdx].

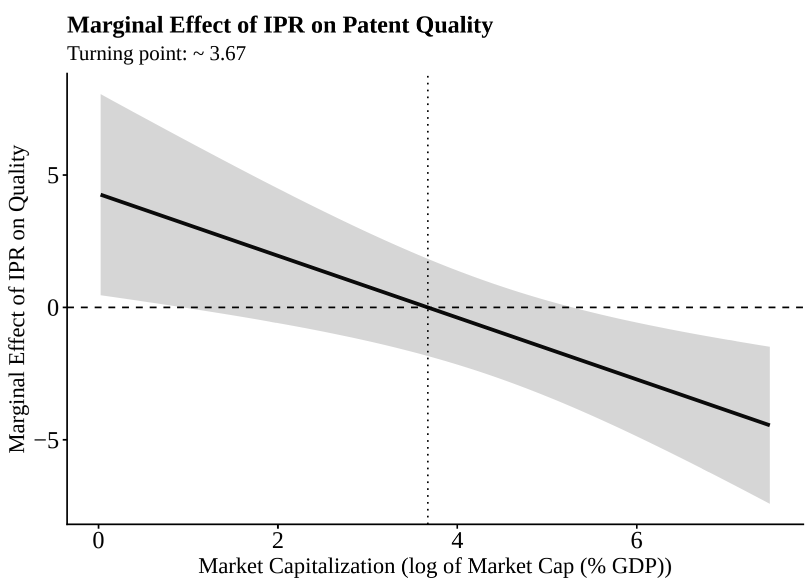

Figure 1: Marginal Effect of Market Finance on Quality at Different IPR Levels

Economically, the magnitudes are meaningful. In Column (4), a one-unit increase in the Park Index raises patent quality by roughly 4.3 points (on a 0-100 scale) when evaluated at the sample mean of financial depth. However, because the interaction coefficient is -1.168, this marginal effect declines as markets deepen. At sufficiently high levels of market capitalization, the net effect of stronger patent protection becomes negative.

The direct effect of market depth itself is modest, but fairly stable. Because market capitalization is log-transformed, a 10% increase in market capitalization corresponds to approximately a 0.10 change in the log term. In Column (4), this implies that a 10% increase in market depth raises patent quality by roughly 0.1 points at average IPR.

Across all specifications, market-based financial development shows a stable, positive association with patent quality, becoming significant at the 5% level in Column (4). IPR strength consistently shows a stable and positive effect on quality, with all specifications reaching some level of significance. Crucially, the interaction term remains negative, stable, and highly significant across all specifications. This robust finding confirms that while patent protection may support quality in financially shallow systems, it exhibits diminishing, and ultimately negative marginal returns as equity markets deepen.

5.2 Bank-Based Finance and Patent Quality

Table 2 reports the five TWFE specifications replacing market capitalization with bank credit. As in the market regressions, country and year fixed effects are included throughout. The bank–quality results do not display the stability or economic credibility observed in the market models.

Table 2: Bank Finance and Patent Quality

	Dependent variable:				
	Patent Quality				
	(1)	(2)	(3)	(4)	(5)
Bank Credit	−1.162*	−0.989	−0.910	0.213	−0.397
	(0.705)	(0.752)	(0.710)	(0.766)	(0.884)
IPR Strength	−1.297	−1.065	−1.907	5.569**	3.667
	(2.874)	(2.993)	(3.376)	(2.283)	(2.758)
Bank Credit × IPR	0.481	0.446	0.648	−1.236**	−0.722
	(0.888)	(0.834)	(0.915)	(0.538)	(0.698)
GDP per Capita (log)		−0.693	−0.988	−1.668	−1.655
		(2.532)	(2.356)	(1.089)	(1.021)
Trade Openness			3.016	−0.447	−1.335
			(1.946)	(1.236)	(1.526)
R&D Expenditure				1.487	2.405
				(1.412)	(1.894)
Tertiary Education					−0.594
					(0.889)
Observations	1,329	1,308	1,302	920	723
R^2	0.010	0.008	0.019	0.017	0.012
Adjusted R^2	−0.067	−0.069	−0.060	−0.075	−0.111

Note: *p<0.1; **p<0.05; ***p<0.01
Country & Year FE included. Clustered SE in parentheses.

In contrast to the market-based results, the relationship between bank finance and patent quality is weaker and less stable. Coefficients on bank credit vary across specifications and are not consistently distinguishable from zero. The interaction between bank finance and IPR strength does not display the same sign stability observed for market-based finance, and economic magnitudes and significance are unstable, relative to those estimated for equity markets.

While banks play a critical role in overall economic activity, the evidence here does not indicate that deeper banking systems are strongly associated with improvements in patent quality.

5.3 Venture Capital and Patent Quality

Estimates using venture capital investment as the financial channel are reported in Table A.2 (see Appendix). Relative to the market and bank regressions, sample size declines meaningfully due to data availability

The coefficients on venture capital and its interaction with IPR are not consistently statistically significant and exhibit sensitivity to controls. While venture capital is often linked to high-growth entrepreneurial firms at the micro level, the cross-country aggregate variation captured in this panel does not reveal a stable relationship between overall VC investment and average patent quality.

The results across financial channels indicate that the most robust and economically meaningful association with patent quality emerges for market-based finance, particularly through its interaction with patent protection.

5.4 Innovation Quantity

To distinguish quality from scale, I next examine patent quantity per researcher as the dependent variable. Tables A.3, 3, and A.4 report the corresponding TWFE estimates. Because the dependent variable is logged, coefficients can be interpreted as elasticities. The most meaningful results concern Table 3

Table 3: Bank Finance and Patent Quantity

	Dependent Variable: ln(Patents per 1,000 Researchers)				
	ln_patents				
	(1)	(2)	(3)	(4)	(5)
ln_bank	0.085	0.021	0.022	−0.004	0.186
	(0.142)	(0.166)	(0.166)	(0.161)	(0.210)
ipr_c	−0.611	−0.426	−0.468	−0.629	−1.427*
	(0.921)	(0.661)	(0.635)	(0.652)	(0.801)
ln_bank_x_ipr	0.286	0.156	0.166	0.206	0.379**
	(0.287)	(0.165)	(0.158)	(0.158)	(0.186)
ln_gdp_pc		1.276**	1.289**	1.379**	1.147**
		(0.620)	(0.619)	(0.624)	(0.503)
ln_trade			0.108	0.149	0.208
			(0.286)	(0.283)	(0.291)
ln_rd				−0.462	−0.631
				(0.552)	(0.442)
ln_tertiary					0.514*
					(0.269)
Observations	813	801	801	800	614
R^2	0.125	0.219	0.220	0.228	0.370
Adjusted R^2	0.036	0.138	0.138	0.146	0.279

Note: *p<0.1; **p<0.05; ***p<0.01
Country and year fixed effects included in all models.
Standard errors clustered by country.

For bank-based finance, all specifications show a positive interaction between bank credit and

IPR for patent quantity. This pattern contrasts with the quality results and suggests that stronger patent protection in deeper bank-oriented systems may expand patenting activity along the extensive margin without necessarily increasing average technological value.

For market-based finance, neither the main effect nor the interaction with IPR displays the same consistent and economically meaningful pattern observed for patent quality. The interaction between equity market depth and patent protection that appears prominently in the quality regressions does not replicate for patent quantity.

Venture capital exhibits a negative association with patent quantity in some specifications, though these estimates are sensitive to controls, as well as sample size, and should therefore be interpreted cautiously.

The key implication is that financial structure and patent protection affect different dimensions of innovation differently. The strongest and most stable interaction appears for patent quality rather than patent quantity, supporting a compositional interpretation of innovation rather than a purely scale-based one.

Figure A.5 illustrates the relationship between patent quantity and average quality across country-years, reinforcing the importance of distinguishing between these two margins.

5.5 Frontier Innovation: Breakthrough Patents

Tables 4, A.5, and A.6 present ZINB models of breakthrough patents. These models separate the innovation process into (i) a selection equation governing structural non-participation and (ii) an intensity equation governing breakthrough production conditional on participation. Intensity coefficients are interpreted as log-rate effects on expected breakthroughs per patent (with exponentiated values indicating percentage changes), while selection coefficients reflect log-odds effects on the probability of structural non-participation.

Across all specifications and financial channels, the dispersion parameter (log theta) is statistically significant, confirming substantial overdispersion and justifying the use of the negative binomial framework.

Because these models do not include country and year fixed effects, they are interpreted as complementary rather than causal within-country estimates. Still, the results mirror the central finding: financial and legal regimes shape innovation across the quality spectrum, including the upper tail of breakthrough activity.

Table 4: ZINB: Market Finance and Breakthroughs

Intensity: Negative Binomial Count	Model 1	Model 2	Model 3	Model 4
Intercept (Count)	-9.415***	-9.275***	-9.801***	-9.515***
	(0.761)	(0.732)	(0.802)	(0.988)
IPR Strength	-0.457***	-0.523***	-0.539***	-0.611***
	(0.062)	(0.062)	(0.148)	(0.182)
Market Cap	-0.064	-0.014	0.206	0.085
	(0.051)	(0.052)	(0.166)	(0.201)
Market Cap × IPR	0.215***	0.160**	-0.024	0.098
	(0.061)	(0.062)	(0.176)	(0.218)
GDP per Capita	0.372***	0.485***	0.399***	0.196*
	(0.074)	(0.074)	(0.090)	(0.106)
Trade Openness		-0.310***	-0.178**	0.051
		(0.051)	(0.077)	(0.111)
R&D Expenditure			0.756***	0.836***
			(0.160)	(0.180)
Tertiary Education				0.175
				(0.161)
Log Theta	0.491***	0.616***	0.750***	0.782***
	(0.079)	(0.085)	(0.106)	(0.131)
Selection: Logit Structural Zero	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Intercept (Zero)	12.733**	12.296*	15.356	15.713
	(5.280)	(7.049)	(19.037)	(14.055)
GDP per Capita (Selection)	-1.820**	-1.819*	-2.334	-2.307
	(0.709)	(0.972)	(2.734)	(1.993)
Num.Obs.	1450	1450	890	641

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Standard errors in parentheses.

Log Theta represents the natural logarithm of the negative binomial dispersion parameter, estimated directly.

In the market specification, the selection equation shows that higher GDP per capita reduces the probability of structural exclusion from frontier innovation. As controls are added and the sample narrows, statistical significance weakens, though signs and magnitude remain stable.

Because the intensity equation conditions on countries already capable of producing frontier innovation, these results effectively reflect the financially advanced segment of the TWFE interaction curve. The consistently negative IPR coefficient therefore reinforces the earlier finding that in financially mature systems, stronger patent protection is associated with lower-quality innovation outcomes. While the interaction between market depth and IPR may be positive in certain specifications, this may reflect attenuation rather than reversal. The net marginal effect of IPR remains negative at higher levels of financial depth.

The bank-based ZINB specification (see Table A.5) exhibits greater instability. While IPR remains negative and statistically significant in the intensity equation across specifications, other coefficients show sensitivity to controls and sample size. Although the negative IPR coefficient aligns directionally with the other findings, coefficient instability suggests caution in drawing strong conclusions from this table.

Despite smaller samples, the venture capital models (see Table A.5) yields a clearer pattern, similar to the market results. The selection equation consistently indicates that higher GDP per capita reduces structural exclusion from frontier innovation.

In the intensity equation, IPR strength is negative and statistically significant across specifications. The interaction between VC depth and IPR is positive across columns but does not overturn the negative baseline effect of IPR.

As with the market specification, because the intensity equation conditions on frontier-capable economies, these results represent the advanced portion of the TWFE interaction curve. The consistently negative IPR coefficient reinforces the central finding: in financially mature systems, stronger patent protection is associated with reduced breakthrough intensity per patent.

6 Summary and Final Thoughts

A Appendix: Supplementary Tables and Figures

A.1 Supplementary Specifications

Baseline Two-Way Fixed Effects (TWFE):

$$Y_{it} = \beta_0 + \beta_1 FD_{it} + \beta_2 IPR_{it} + \beta_3 (FD_{it} \times IPR_{it}) + \mathbf{X}'_{it}\beta + \alpha_i + \lambda_t + \varepsilon_{it} \tag{1}$$

ZINB Selection Equation (Structural Zeros):

$$\ln\left(\frac{\pi_{it}}{1 - \pi_{it}}\right) = \gamma_0 + \gamma_1 \ln(\text{GDP per capita}_{it}) \tag{2}$$

ZINB Intensity Equation (Count Margin):

$$\ln(\mu_{it}) = \beta_0 + \beta_1 FD_{it} + \beta_2 IPR_{it} + \beta_3 (FD_{it} \times IPR_{it}) + \mathbf{X}' it\beta + \ln(\text{Patents}_{it}) \tag{3}$$

A.2 Supplementary Tables

Table A.1: Descriptive Statistics

Variable	Unique	Missing %	Mean	SD	Min	Median	Max
Breakthrough Count	99	0	4.85	20.96	0.00	0.00	264.00
Patent Quality Index	2575	7	26.23	6.46	4.29	26.27	68.45
Patent Quantity (log)	1097	61	3.63	1.04	0.36	3.61	6.63
Market Finance (log)	1742	37	3.76	1.06	0.02	3.79	7.48
Bank Finance (log)	1746	37	4.22	0.67	2.06	4.28	5.72
Venture Capital (log)	637	77	1.52	0.98	0.00	1.38	6.17
IPR Strength (Centered)	157	30	-0.00	1.05	-3.24	0.30	1.56
GDP per Capita (log)	2440	12	9.86	0.96	5.98	10.03	12.03
Trade Openness (log)	2350	16	4.32	0.65	2.31	4.26	6.09
R&D Expenditure (log)	1332	52	0.82	0.40	0.04	0.78	1.95
Tertiary Enrollment (log)	1343	52	3.92	0.62	0.94	4.11	5.12

Table A.2: Venture Capital and Patent Quality

	Dependent Variable: Patent Quality (0–100)				
	quality_index_100				
	(1)	(2)	(3)	(4)	(5)
ln_vc	−0.517	−0.388	−0.354	−0.404	−0.259
	(0.550)	(0.529)	(0.522)	(0.608)	(0.712)
ipr_c	−0.029	0.222	0.286	0.354	0.688
	(1.041)	(0.988)	(1.032)	(1.189)	(0.980)
ln_vc_x_ipr	0.071	−0.087	−0.119	−0.088	−0.059
	(0.701)	(0.723)	(0.754)	(0.849)	(0.828)
ln_gdp_pc		−1.810	−1.844	−1.986	−3.793
		(2.292)	(2.269)	(2.222)	(2.862)
ln_trade			0.401	−0.118	0.953
			(1.975)	(2.050)	(2.306)
ln_rd				1.191	0.718
				(1.702)	(2.089)
ln_tertiary					−3.656
					(2.236)
Observations	428	428	428	408	358
R^2	0.005	0.008	0.008	0.009	0.024
Adjusted R^2	−0.121	−0.121	−0.124	−0.133	−0.142

Note: *p<0.1; **p<0.05; ***p<0.01
Country and year fixed effects included in all models.
Standard errors clustered by country.

Table A.3: Market Finance and Patent Quantity

	Dependent variable:				
	Log Patents				
	(1)	(2)	(3)	(4)	(5)
Market Cap	0.077	−0.023	−0.019	−0.027	0.124
	(0.079)	(0.102)	(0.100)	(0.095)	(0.157)
IPR Strength	−0.073	−0.207	−0.205	−0.246	−0.383
	(0.246)	(0.266)	(0.263)	(0.260)	(0.356)
Market Cap × IPR	0.060	0.065	0.064	0.076	0.086
	(0.081)	(0.077)	(0.075)	(0.066)	(0.103)
GDP per Capita (log)		0.968	0.955	0.989^{*}	0.759
		(0.635)	(0.607)	(0.601)	(0.576)
Trade Openness			−0.039	−0.028	−0.298
			(0.313)	(0.320)	(0.408)
R&D Expenditure				−0.240	−0.798
				(0.649)	(0.524)
Tertiary Education					0.759^{***}
					(0.258)
Observations	756	754	754	754	533
R^2	0.017	0.070	0.070	0.072	0.243
Adjusted R^2	−0.088	−0.030	−0.031	−0.031	0.121
Note:	*p<0.1; **p<0.05; ***p<0.01				
	Country & Year FE included. Clustered SE in parentheses.				

Table A.4: Venture Capital and Patent Quantity

	Dependent Variable: ln(Patents per 1,000 Researchers)				
	ln_patents				
	(1)	(2)	(3)	(4)	(5)
ln_vc	−0.215**	−0.222**	−0.193**	−0.126	−0.002
	(0.102)	(0.091)	(0.089)	(0.084)	(0.073)
ipr_c	−0.338	−0.359*	−0.322	−0.343*	−0.218
	(0.250)	(0.214)	(0.204)	(0.183)	(0.156)
ln_vc_x_ipr	0.155	0.163	0.136	0.072	−0.015
	(0.111)	(0.111)	(0.117)	(0.123)	(0.111)
ln_gdp_pc		0.142	0.118	0.459*	0.775***
		(0.401)	(0.401)	(0.278)	(0.230)
ln_trade			0.351	0.502	0.220
			(0.415)	(0.408)	(0.326)
ln_rd				−0.962*	−0.719*
				(0.498)	(0.389)
ln_tertiary					0.225
					(0.270)
Observations	375	375	375	375	329
R^2	0.039	0.040	0.051	0.122	0.082
Adjusted R^2	−0.099	−0.101	−0.093	−0.014	−0.083

Note: *p<0.1; **p<0.05; ***p<0.01
Country and year fixed effects included in all models.
Standard errors clustered by country.

Table A.5: ZINB: Bank Development and Breakthroughs

Intensity: Negative Binomial Count	Model 1	Model 2	Model 3	Model 4
Intercept (Count)	-9.453***	-9.553***	-9.948***	-8.927***
	(0.761)	(0.721)	(0.689)	(0.973)
IPR Strength	-0.509***	-0.491***	-0.636***	-0.597***
	(0.071)	(0.070)	(0.136)	(0.161)
Bank Credit	0.207**	0.156	-0.030	-0.205
	(0.097)	(0.098)	(0.190)	(0.217)
Bank Credit × IPR	0.143	-0.023	0.456**	0.686***
	(0.096)	(0.102)	(0.193)	(0.226)
GDP per Capita	0.373***	0.528***	0.355***	0.069
	(0.074)	(0.075)	(0.084)	(0.105)
Trade Openness		-0.352***	-0.044	0.254**
		(0.056)	(0.084)	(0.112)
R&D Expenditure			0.722***	0.961***
			(0.155)	(0.173)
Tertiary Education				0.059
				(0.158)
Log Theta	0.590***	0.716***	0.769***	0.795***
	(0.089)	(0.094)	(0.106)	(0.121)
Selection: Logit Structural Zero	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Intercept (Zero)	11.465***	10.419	832.493	17.435
	(4.165)	(6.481)	(1195.555)	(10.774)
GDP per Capita (Selection)	-1.629***	-1.587*	-124.179	-2.464
	(0.554)	(0.898)	(178.258)	(1.526)
Num.Obs.	1337	1331	929	728

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Standard errors in parentheses.

Log Theta represents the natural logarithm of the negative binomial dispersion parameter, estimated directly.

Table A.6: ZINB: Venture Capital and Breakthroughs

Intensity: Negative Binomial Count	Model 1	Model 2	Model 3	Model 4
Intercept (Count)	-8.201***	-8.403***	-10.171***	-8.844***
	(1.618)	(1.631)	(1.986)	(2.939)
IPR Strength	-0.887***	-0.932***	-0.901***	-0.636**
	(0.192)	(0.198)	(0.228)	(0.256)
Venture Capital	-0.049	-0.042	-0.154	-0.024
	(0.145)	(0.145)	(0.164)	(0.178)
Venture Capital × IPR	0.434***	0.405***	0.469***	0.358*
	(0.146)	(0.150)	(0.162)	(0.186)
GDP per Capita	0.283*	0.342**	0.428**	0.202
	(0.148)	(0.162)	(0.190)	(0.233)
Trade Openness		-0.087	-0.040	0.083
		(0.100)	(0.106)	(0.128)
R&D Expenditure			0.507**	0.483*
			(0.230)	(0.253)
Tertiary Education				0.056
				(0.262)
Log Theta	1.015***	1.021***	1.015***	0.994***
	(0.136)	(0.137)	(0.139)	(0.146)
Selection: Logit Structural Zero	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Intercept (Zero)	39.580***	38.812***	36.476***	52.394***
	(9.254)	(9.304)	(11.430)	(18.440)
GDP per Capita (Selection)	-4.166***	-4.093***	-3.914***	-5.502***
	(0.940)	(0.944)	(1.160)	(1.936)
Num.Obs.	428	428	408	358

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Standard errors in parentheses.

Log Theta represents the natural logarithm of the negative binomial dispersion parameter, estimated directly.

A.3 Supplementary Figures

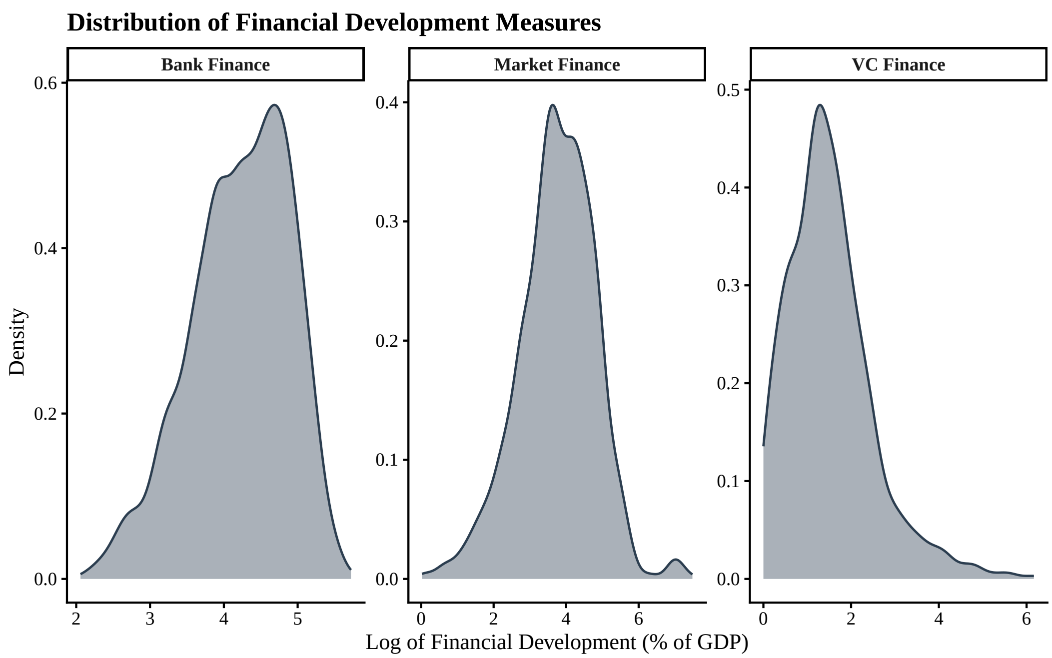

Figure A.1: Financial Development Distributions

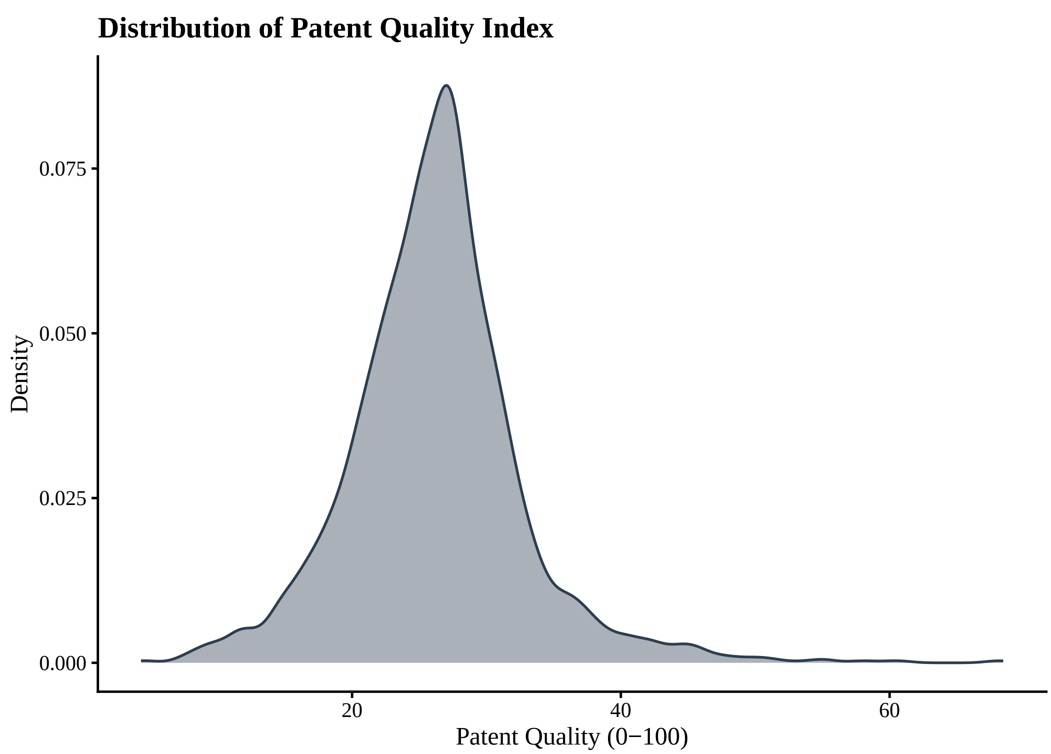

Figure A.2: Patent Quality Density by Variable

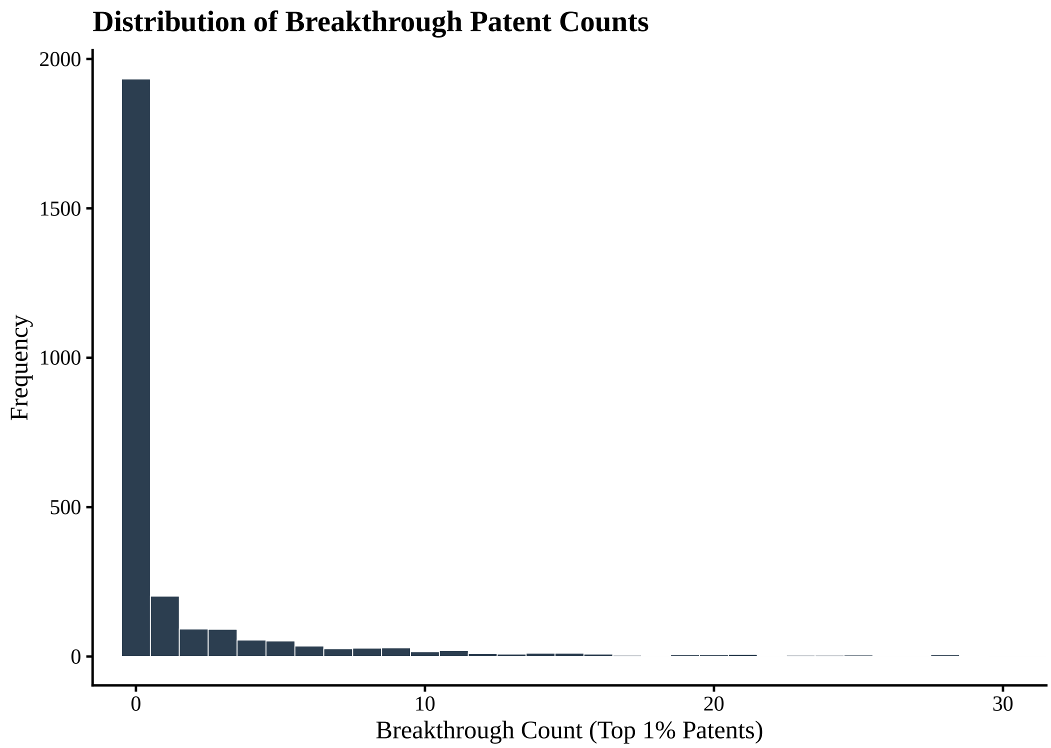

Figure A.3: Breakthrough Patent Distribution

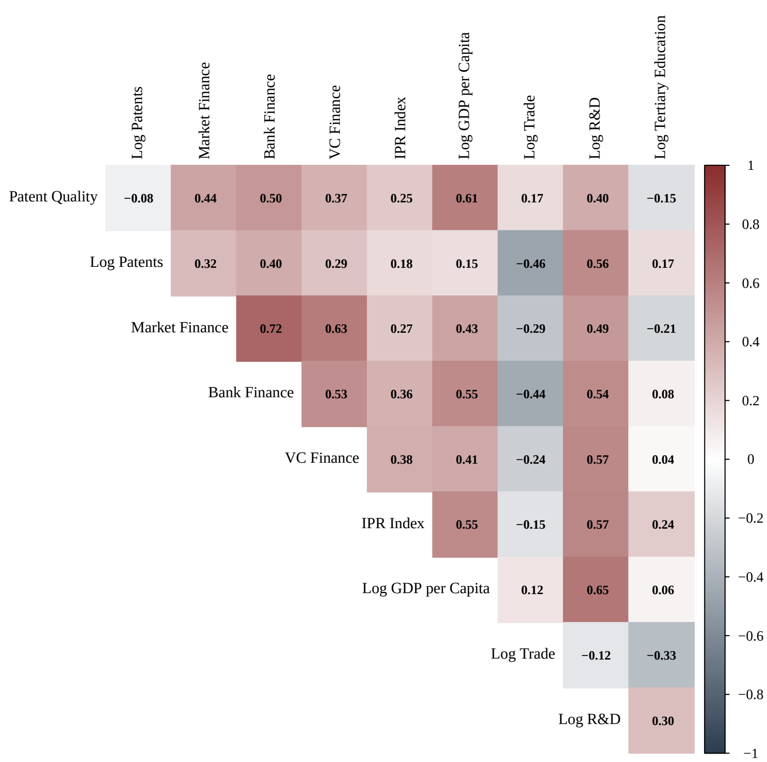

Figure A.4: Correlation Matrix of Key Variables

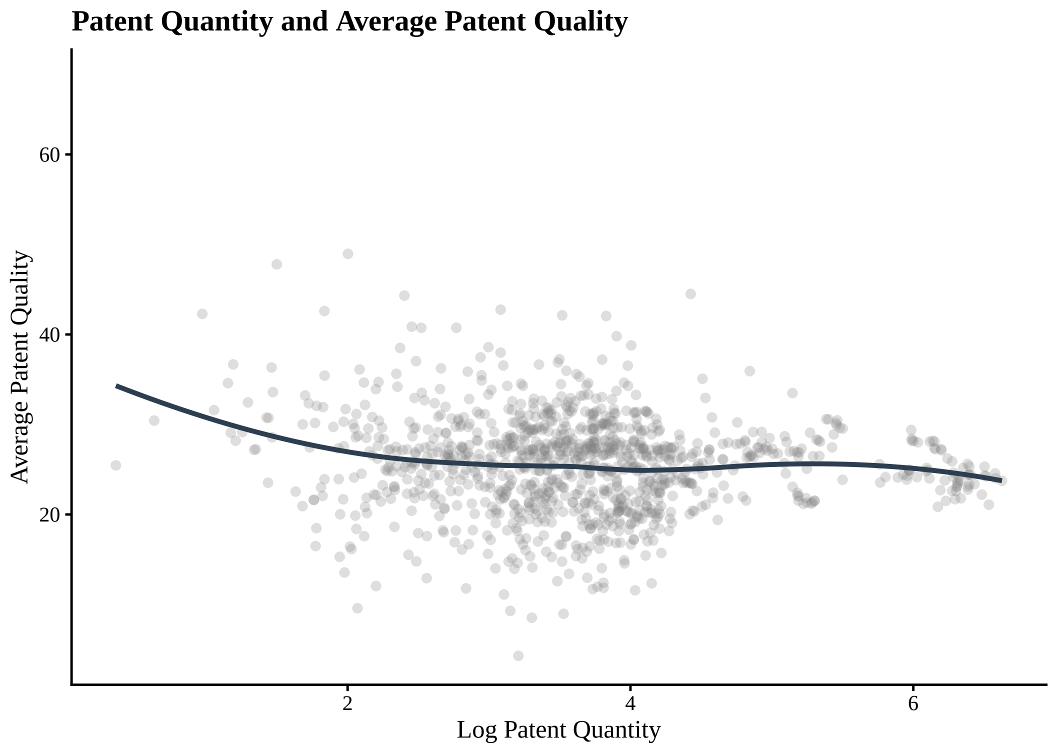

Figure A.5: Patent Quality vs. Patent Quantity

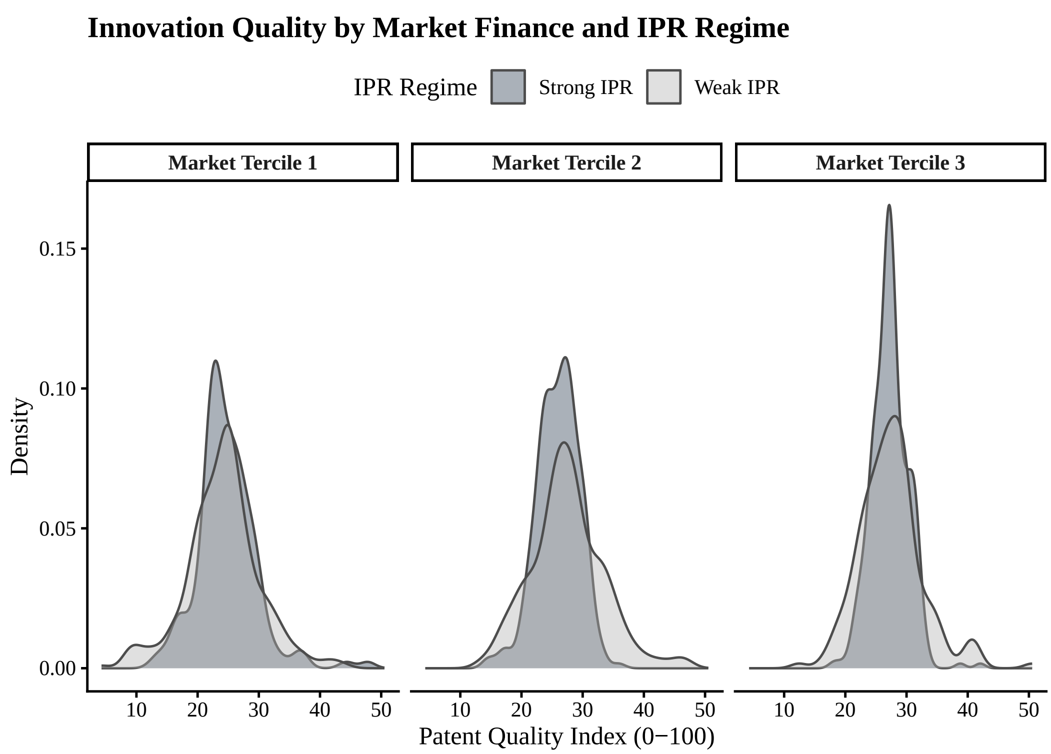

Figure A.6: Innovation Quality by Financial Regime

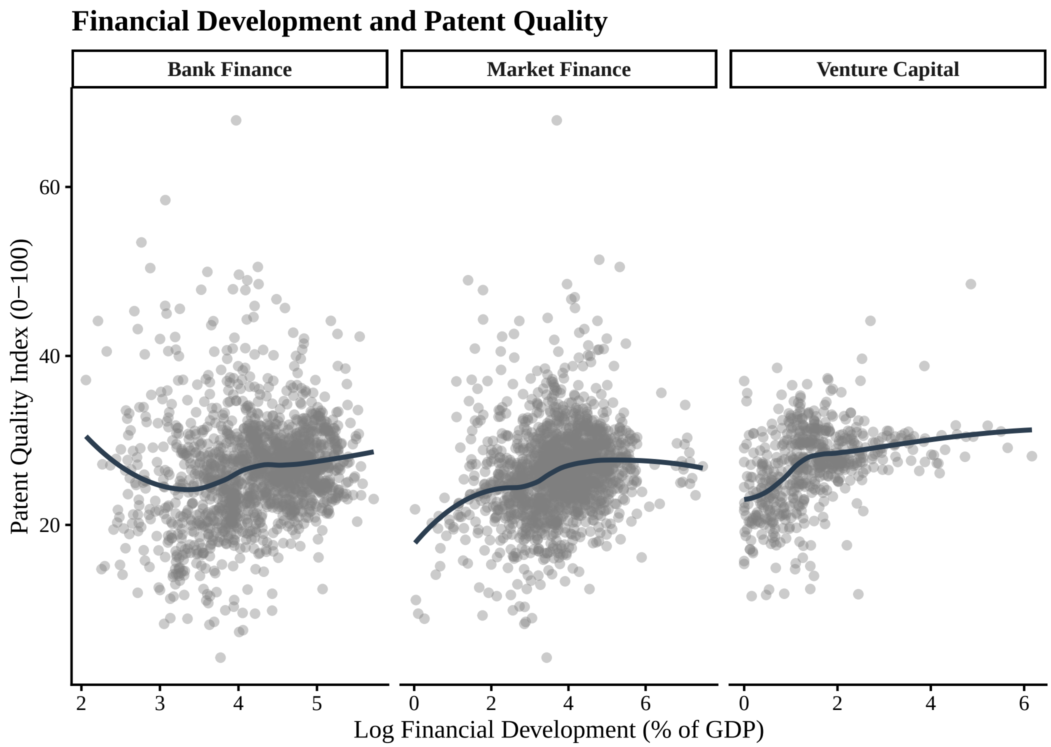

Figure A.7: Scatter: Financial Development and Quality

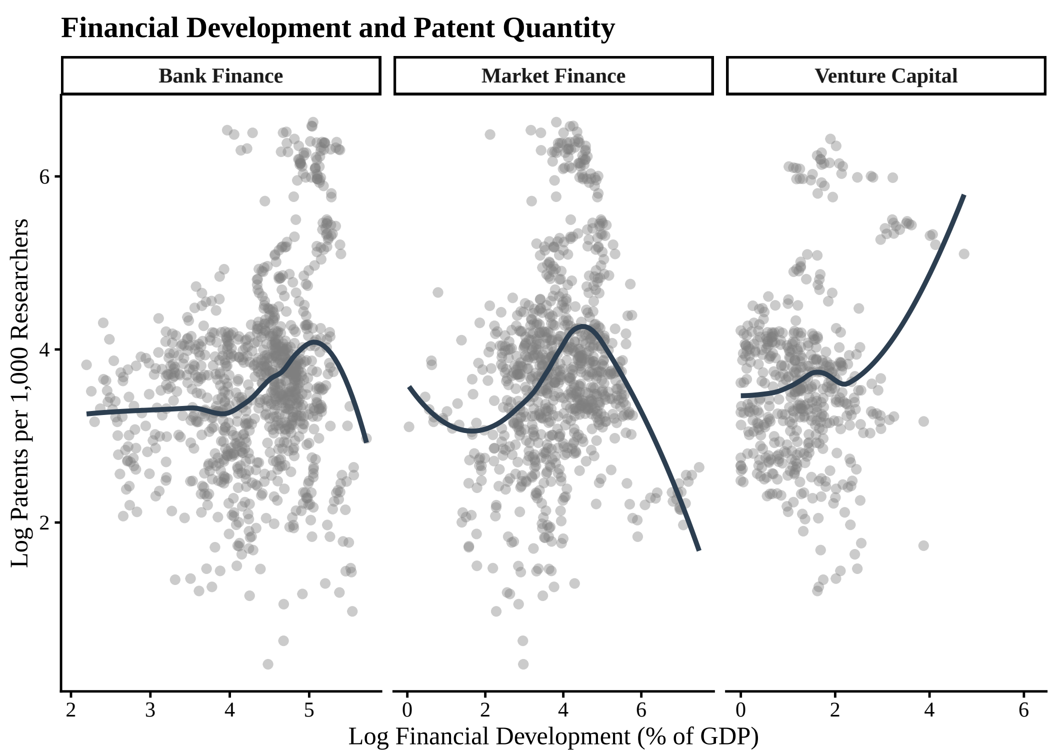

Figure A.8: Scatter: Financial Development and Quantity

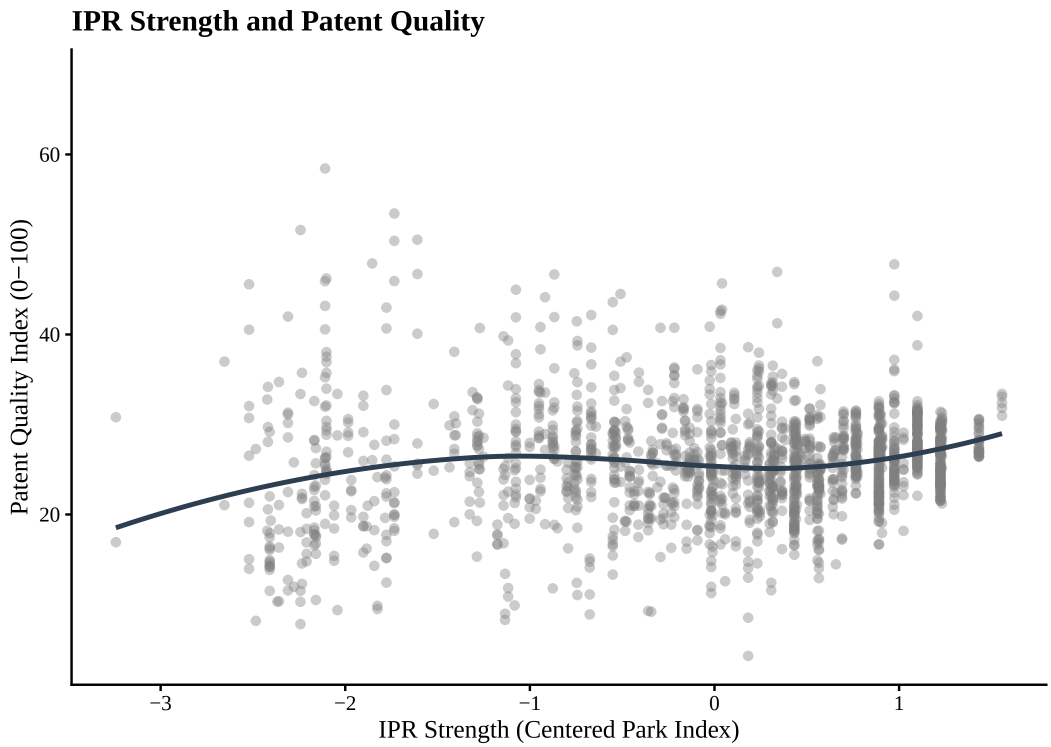

Figure A.9: Scatter: IPR Strength and Quality

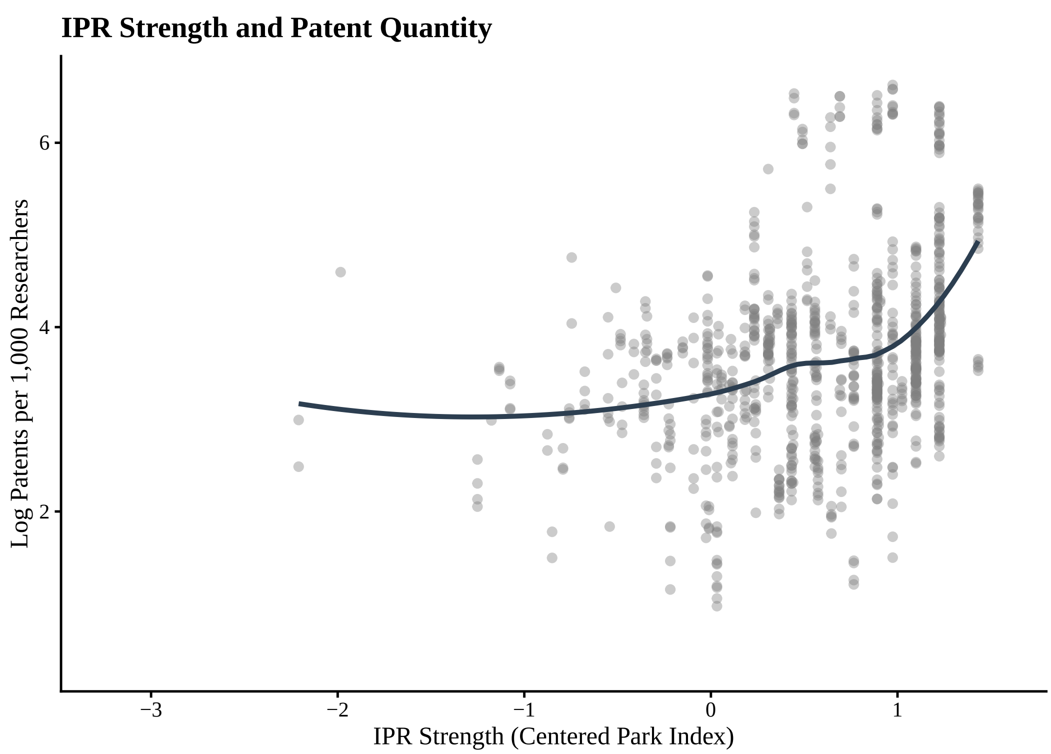

Figure A.10: Scatter: IPR Strength and Quantity

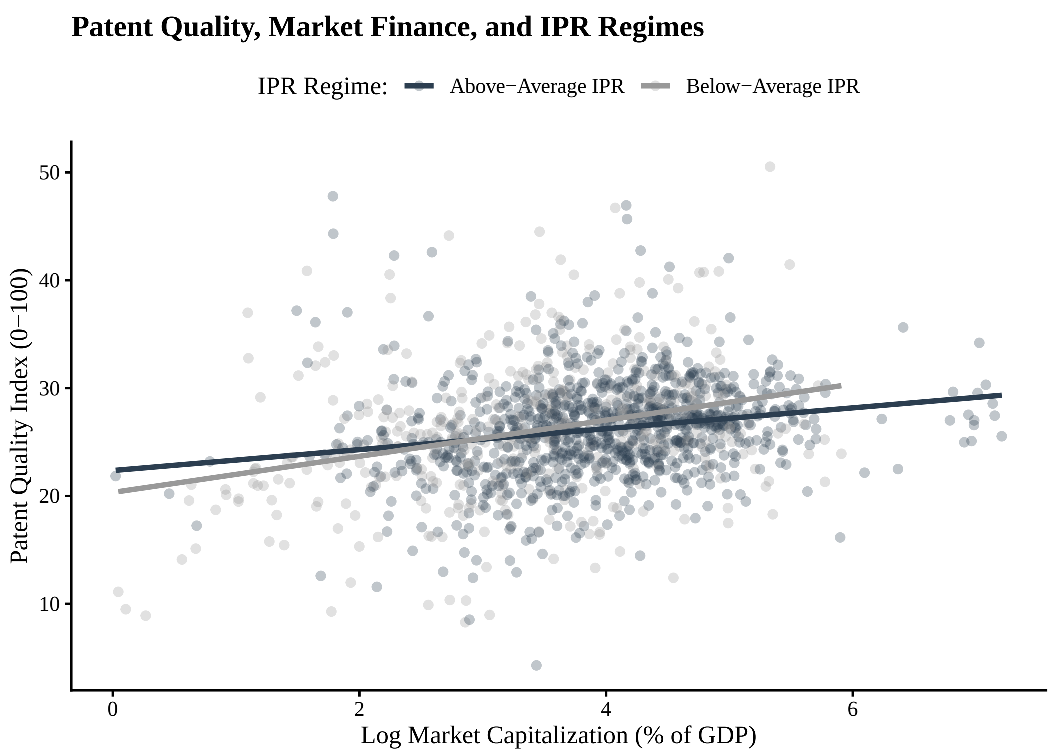

Figure A.11: Binned Interaction Scatterplot

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„Die Lust der Zerstörung ist zugleich eine schaffende Lust.“

Mikhail Bakunin

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