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 the marginal effect of stronger patent protection on patent quality declines as public equity markets deepen, becoming negative in advanced systems. Stricter IPR regimes, particularly in deeper financial environments, are associated with greater patenting intensity, while supplementary breakthrough models reveal a consistently negative association between stronger patent protection and frontier innovation. 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, Klein and Yang, 2025]. 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. To my knowledge, no prior cross-country study has jointly examined financial structure, IPR strength, and innovation composition using patent-quality indicators and breakthrough modeling. 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 results concern equity market development. Deeper equity markets are modestly positively associated with higher patent quality. However, 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. 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.

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. 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 a summary of this paper, and some final thoughts.

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]. 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:

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

where Y_{it} denotes either: Average patent quality (OECD composite index), or Log patents per capita times one million. FD^c_{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. Institutional variables are mean centered for ease of interpretation.

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 Greene [1994].

Following a standard ZINB framework [UCLA Statistical Consulting Group, 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:

$$\ln(\mu_{it}) = \zeta_0 + \zeta_1 FD_{it}^c + \zeta_2 IPR_{it}^c + \zeta_3(FD_{it}^c \times IPR_{it}^c) + \mathbf{X}_{it}'\zeta + \ln(\text{Patents}_{it}) \tag{3}$$

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 construct a measure of patent quantity defined as resident patent applications per capita, scaled per one million inhabitants and expressed in logarithmic form. Normalizing by population mitigates pure country size effects and allows the dependent variable to capture patenting intensity relative to economic scale rather than absolute population size.

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. All FD variables are mean-centered to facilitate interpretation of main effects in the presence of interaction terms.

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 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 two-way fixed effects specifications corresponding to equation (1). Column (1) includes only the financial and institutional variables. Columns (2) through (5) incrementally introduce macroeconomic controls, while country and year fixed effects are retained throughout. The discussion focuses primarily on Columns (3) and (4), which balance sample size and covariate inclusion.

Table 1: Market Finance and Patent Quality

	Dependent variable:				
	Average Patent Quality (0–100)				
	(1)	(2)	(3)	(4)	(5)
$\ln(\text{Market Cap}/GDP)^c$	0.390	0.364	0.390	0.975^{**}	0.602
	(0.281)	(0.300)	(0.316)	(0.396)	(0.632)
IPR Strength^c	-0.696	-0.505	-0.505	-0.103	-0.099
	(0.560)	(0.530)	(0.533)	(0.927)	(0.762)
Market Cap^c $\times$ IPR^c	-0.651^{***}	-0.676^{***}	-0.685^{***}	-1.168^{***}	-1.053^{**}
	(0.229)	(0.232)	(0.232)	(0.394)	(0.430)
ln(GDP per Capita)		-0.788	-0.837	-2.337^{*}	-0.819
		(1.821)	(1.856)	(1.386)	(1.678)
ln(Trade Openness)			-0.443	-0.515	-1.299
			(1.273)	(1.834)	(1.900)
ln(R&D Expenditure)				-0.432	-1.372
				(1.615)	(2.344)
ln(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
Note:	*p<0.1; **p<0.05; ***p<0.01				
	Country & Year FE included. Clustered SE in parentheses.				
	Continuous variables log-transformed + 1; FD, IPR mean-centered				

Because both financial development and IPR strength are mean-centered prior to interaction, the coefficient on IPR^c represents the marginal effect of stronger patent protection evaluated at the sample mean level of financial depth. Likewise, the coefficient on $\ln(\text{Market Cap}/GDP)^c$ represents the effect of financial deepening evaluated at the mean level of patent protection.

In Column (3), the interaction between financial depth and IPR strength is negative and highly significant ($\beta = -0.685$, $p < 0.01$). The marginal effect of IPR on patent quality is given by:

$$\frac{\partial \text{Quality}}{\partial \text{IPR}} = \beta_{\text{IPR}} + \beta_{\text{Interaction}} \cdot FD^c$$

Setting this derivative equal to zero yields the turning point:

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

Using Column (3) coefficients ($\beta_{\text{IPR}} = -0.505$, $\beta_{\text{Interaction}} = -0.685$), the threshold occurs at: $FD^{c*} \approx -0.737$.

Because financial development is centered, this corresponds to a level approximately 0.74 log-units *below* the sample mean. Given the summary statistics (mean ≈ 3.76, SD = 1.06), the turning point lies roughly 0.7 standard deviations below the average level of financial depth. Converting back to levels: $FD^* = 3.76 - 0.737 \approx 3.02$, which implies market capitalization of approximately $e^{3.02} - 1 \approx 19.5\%$ of GDP. Thus, even in moderately developed financial systems, the marginal effect of stronger IPR on average patent quality becomes negative.

Column (4) introduces R&D expenditure, reducing the sample from 1,422 to 880 country-years. This restriction excludes lower-income economies with missing R&D data, effectively shifting the sample toward more innovation-intensive countries. In this specification, the interaction term becomes even larger in magnitude ($\beta = -1.168$, $p < 0.01$), while the baseline IPR coefficient moves closer to zero ($\beta = -0.103$). Recomputing the threshold: $FD^{c*} = -\frac{-0.103}{-1.168} \approx -0.088$. This implies that the marginal effect of IPR becomes negative just 0.09 log-units below the sample mean (effectively at the mean level of financial development). Converting back: $FD^* \approx 3.76 - 0.088 = 3.67$, which corresponds to market capitalization of roughly $e^{3.67} - 1 \approx 38\%$ of GDP. Because this threshold lies extremely close to the sample mean and median, the net marginal effect of stronger patent protection is negative for approximately half of the observed country-years in the R&D-restricted sample.

Evaluated at the sample mean ($FD^c = 0$), the coefficient on IPR^c in Column (3) implies that a one-unit increase in the Park Index reduces average patent quality by 0.505 points on the 100-point scale. Given the standard deviation of IPR (1.05), a one-standard-deviation increase in patent protection is associated with a decline of approximately 0.53 quality points at mean financial depth. In Column (4), the baseline IPR effect is economically small and statistically insignificant, but the interaction remains large and highly stable, indicating that the substitution effect between financial deepening and patent protection drives the results.

The direct effect of financial development itself is positive but modest. In Column (4), a one-standard-deviation increase in centered log financial depth (SD = 1.06) is associated with an increase of approximately $0.975 \times 1.06 \approx 1.03$ points in average patent quality when evaluated at mean IPR. This suggests that equity market expansion modestly supports higher-quality innovation, but only in institutional environments where patent protection is not excessively restrictive.

Crucially, the interaction term remains negative, stable, and highly significant across all five specifications. A joint Wald test in Column (4) rejects the null that financial depth and the interaction are jointly zero ($p = 0.0032$). Figure 1 illustrates this substitution pattern graphically. As public equity markets deepen, stronger patent protection transitions from potentially neutral to systematically harmful for average patent quality.

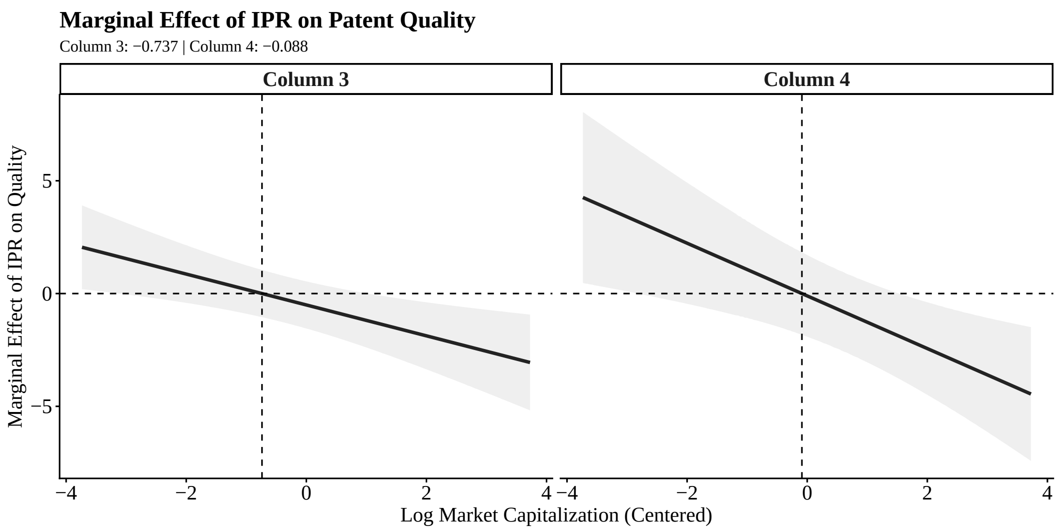

Figure 1: Marginal Effects: IPR Strenth on Patent Quality, Market Finance

The evidence indicates that while financial development may independently support higher-quality innovation, its coexistence with strict intellectual property regimes generates diminishing, and ultimately negative marginal returns to patent protection.

5.2 Bank-Based Finance and Patent Quality

Table A.2 reports the five TWFE specifiations 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.

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.3 (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

Table A.4 reports two-way fixed effects estimates examining the relationship between equity market development, intellectual property rights, and patent intensity, measured as ln(Patents per Capita) $\times$ $1e6$, where patents per capita are computed as resident patent applications divided by total population and scaled per million inhabitants.

Table 2: Market Finance and Patent Quantity

	Dependent variable:				
	ln(Patents per Capita)				
	(1)	(2)	(3)	(4)	(5)
ln(Market Cap/GDP)^c	0.095	−0.070	−0.085	−0.135*	0.011
	(0.096)	(0.081)	(0.079)	(0.081)	(0.110)
IPR Strength^c	0.491***	0.158	0.153	0.109	0.086
	(0.177)	(0.124)	(0.121)	(0.118)	(0.161)
Market^c × IPR^c	0.194**	0.132**	0.133**	0.180***	0.174**
	(0.079)	(0.062)	(0.062)	(0.046)	(0.069)
ln(GDP per Capita)		2.419***	2.460***	1.360***	0.771**
		(0.545)	(0.550)	(0.491)	(0.374)
ln(Trade Openness)			0.208	−0.021	−0.312
			(0.216)	(0.238)	(0.267)
ln(R&D Expenditure)				1.053*	0.756*
				(0.606)	(0.458)
ln(Tertiary Education)					0.929***
					(0.249)
Observations	1,334	1,329	1,329	841	598
R^2	0.096	0.355	0.357	0.210	0.385
Note:	*p<0.1; **p<0.05; ***p<0.01				
	Country & Year FE included. Clustered SE in parentheses.				
	Continuous variables log-transformed + 1; FD, IPR mean-centered				

Because the dependent variable is in logs, coefficients are interpreted as semi-elasticities: a one-unit change in an independent variable corresponds to an approximate percentage change in patents per capita.

Financial development and IPR strength are mean-centered prior to interaction. Accordingly, the coefficient on IPR^c represents the marginal effect of stronger patent protection evaluated at the sample mean level of market development, while the coefficient on ln(Market Cap/GDP)^c reflects the effect of financial deepening at the mean level of IPR strength.

Columns (3) and (4) are the primary subjects in this discussion. In Column (3), the interaction between market depth and IPR strength is positive and statistically significant ($\beta = 0.133$, $p < 0.05$).

The marginal effect of IPR on patent intensity is:

$$\frac{\partial \ln(\text{Patents per Capita})}{\partial \text{IPR}} = \beta_{\text{IPR}} + \beta_{\text{Interaction}} \cdot FD^c$$

Using Column (3) coefficients ($\beta_{\text{IPR}} = 0.153$, $\beta_{\text{Interaction}} = 0.133$), the turning point occurs at: $FD^{c*} = -\frac{0.153}{0.133} \approx -1.15$.

Because financial development is centered (SD = 1.06), this threshold lies roughly 1.1 standard deviations below the sample mean. Converting back to levels: $FD^* \approx 3.76 - 1.15 = 2.61$, which corresponds to market capitalization of approximately $e^{2.61} - 1 \approx 13.6\%$ of GDP. Thus, for nearly all economies with moderately developed equity markets, the marginal effect of stronger IPR on patent intensity is positive.

Column (4), which includes R&D expenditure and reduces the sample to 841 country-years, reinforces this pattern. The interaction term increases in magnitude and significance ($\beta = 0.180$, $p < 0.01$), while the baseline IPR effect evaluated at mean financial depth remains positive ($\beta = 0.109$). Recomputing the threshold, $FD^{c*} = -\frac{0.109}{0.180} \approx -0.61$. This lies approximately 0.6 standard deviations below the sample mean, implying that even relatively shallow financial systems cross into the region where stricter patent protection increases patenting intensity.

Economically, the magnitudes are meaningful. In Column (4), a one-unit increase in the Park Index at mean financial depth raises patent intensity by approximately 10.9 percent. A one-standard-deviation increase in IPR strength (SD = 1.05) therefore corresponds to an approximate 11.4 percent increase in patents per capita at mean market development. Moreover, because the interaction is positive, this effect grows larger as equity markets deepen.

In contrast to the quality regressions, where deeper financial systems amplified the negative marginal returns to patent protection, the quantity regressions reveal the opposite dynamic: stronger patent protection and deeper equity markets jointly expand patenting activity, even as average quality declines.

Table 3 reports analogous specifications replacing market capitalization with bank credit as the measure of financial development.

Table 3: Bank Finance and Patent Quantity

	Dependent variable:				
	ln(Patents per Capita)				
	(1)	(2)	(3)	(4)	(5)
ln(Bank Credit/GDP)^c	0.244	−0.017	−0.013	−0.046	0.109
	(0.172)	(0.145)	(0.138)	(0.129)	(0.152)
IPR Strength^c	0.808***	0.244**	0.267**	0.308**	0.268*
	(0.281)	(0.123)	(0.124)	(0.129)	(0.146)
Bank^c × IPR^c	0.402**	0.177	0.112	0.228*	0.275*
	(0.181)	(0.127)	(0.146)	(0.122)	(0.154)
ln(GDP per Capita)		2.135***	2.171***	1.448***	0.985***
		(0.369)	(0.342)	(0.442)	(0.350)
ln(Trade Openness)			−0.320	−0.029	−0.107
			(0.348)	(0.233)	(0.249)
ln(R&D Expenditure)				0.993**	0.873***
				(0.447)	(0.330)
ln(Tertiary Education)					0.704***
					(0.228)
Observations	1,278	1,255	1,249	896	695
R^2	0.188	0.440	0.454	0.366	0.500

Note: *p<0.1; **p<0.05; ***p<0.01
Country & Year FE included. Clustered SE in parentheses.
Continuous variables log-transformed + 1; FD, IPR mean-centered

Across all specifications, the coefficient on IPR^c is positive and statistically significant, particularly in Columns (3) and (4). In Column (4), $\beta_{\text{IPR}} = 0.308$ ($p < 0.05$), implying that at the sample mean level of bank depth, a one-unit increase in the Park Index increases patent intensity by approximately 30.8 percent.

The interaction between bank depth and IPR strength is positive and achieves significance in Columns (1), (4), and (5), though at weaker levels in the fully controlled models. In Column (4), the interaction coefficient is $\beta = 0.228$ ($p < 0.10$). The marginal effect of IPR is:

$$\frac{\partial \ln(\text{Patents per Capita})}{\partial \text{IPR}} = 0.308 + 0.228 \cdot FD^c.$$

The implied turning point occurs at: $FD^{c*} = -\frac{0.308}{0.228} \approx -1.35$. Given the standard deviation of bank depth (0.67), this threshold lies roughly two standard deviations below the sample mean. Converting back to levels: $FD^* \approx 3.76 - 1.35 = 2.41$, which corresponds to bank credit of approximately $e^{2.41} - 1 \approx 11\%$ of GDP. Thus, for virtually the entire observed sample, stricter patent protection increases patenting intensity in bank-oriented systems.

However, unlike the market-based regressions, the baseline coefficient on bank depth itself remains small and statistically insignificant across specifications. This suggests that the expansion of patenting volume is driven primarily by institutional strengthening rather than independent effects of banking deepening.

Venture capital (see A.5) results are weak. In some specifications, VC exhibits a negative association with patent quantity, though these estimates are sensitive to controls, as well as sample size, and should therefore be interpreted cautiously.

5.5 Frontier Innovation: Breakthrough Patents

Tables 4, A.6, and A.7 present the ZINB estimates of breakthrough innovation. Unlike the TWFE specifications, which estimate within-country variation in average outcomes, these models separate the innovation process into two distinct components: (i) a selection equation modeling the probability of structural non-participation in frontier innovation, and (ii) an intensity equation modeling breakthrough production conditional on participation. Because total patenting enters as an offset, these estimates capture breakthrough intensity per patent rather than total frontier output. Also, note that this offset is constructed from granted patents, as covered by the OECD data. It is distinct from the quantity measure derived from patent applications used in the TWFE models.

All financial and institutional variables are mean-centered in the intensity equation. Coefficients in the count component are interpreted as log-rate effects on expected breakthroughs per patent (with exponentiated values corresponding to percentage changes). Coefficients in the selection equation reflect log-odds effects on the probability of structural exclusion.

Across all financial channels and specifications, the dispersion parameter (log theta) is positive and statistically significant at the 1 percent level. This confirms substantial overdispersion in breakthrough counts and justifies the use of the negative binomial model.

Because the ZINB model does not allow inclusion of high-dimensional fixed effects in a straightforward manner, these estimates rely primarily on cross-sectional variation and should not be interpreted as causal.

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-based specification, the selection equation indicates that higher GDP per capita significantly reduces the probability of structural exclusion from frontier innovation. In Columns (1) and (2), the coefficient on log GDP per capita in the selection equation is large, negative, and statistically significant (e.g., $\zeta = -1.820$, $p < 0.05$ in Column 1), implying that wealthier economies are substantially more likely to participate in breakthrough innovation. As additional controls are introduced and the sample narrows (from 1,450 to 641 observations), statistical significance weakens but the sign and magnitude remain stable.

Turning to the intensity equation, the coefficient on IPR strength is negative and highly significant across all specifications, increasing in magnitude as controls are added (from $\zeta = -0.457$ in Column 1 to $\zeta = -0.611$ in Column 4). Because the model employs a log link, exponentiating the fully controlled estimate implies that, evaluated at mean financial depth, a one-unit increase in the Park Index is associated with an approximate $e^{-0.611} - 1 \approx -45.7\%$ reduction in expected breakthroughs per patent.

The intensity equation conditions on countries already capable of producing frontier innovation. In other words, it reflects the financially and technologically advanced segment of the TWFE interaction curve. The consistently negative IPR coefficient therefore reinforces the earlier quality findings: in mature financial systems capable of producing radical innovation, stronger patent protection is associated with lower breakthrough intensity per patent.

The interaction between market depth and IPR is positive and statistically significant in the simpler specifications (Columns 1 and 2), but becomes statistically insignificant once R&D controls are included. Importantly, the interaction never overturns the negative baseline IPR effect in the fully controlled model. Even in financially deep systems, the net marginal effect of stricter patent protection on breakthrough intensity remains negative.

Much like the TWFE quality regressions, where deeper equity markets may modestly lead to improvements in average patent quality, strict intellectual property regimes appear to suppress the upper tail of innovation: the rare, frontier-expanding breakthroughs.

The bank-based ZINB specification (Table A.6) exhibits greater instability. While the intensity equation consistently shows a negative and statistically significant coefficient on IPR strength across all specifications (e.g., $\zeta = -0.597$, $p < 0.01$ in Column 4), other coefficients display sensitivity to controls and sample composition.

Notably, in Model (3) of the selection equation, the intercept and GDP coefficient become extremely large in magnitude with massive standard errors. This pattern is consistent with quasi-complete separation in the logit selection stage, indicating that certain combinations of covariates nearly perfectly predict structural participation in breakthrough innovation. Because of this instability, Model (3)'s estimates should be interpreted accordingly.

In the fully controlled intensity specification (Column 4), the interaction between bank depth and IPR is positive and statistically significant ($\zeta = 0.686$, $p < 0.01$). However, the baseline IPR coefficient remains negative and large in magnitude. Exponentiating the baseline effect implies that, at mean bank depth, a one-unit increase in IPR strength reduces expected breakthrough intensity by approximately $e^{-0.597} - 1 \approx -45\%$. While deeper banking systems may partially ease this effect, they do not reverse it.

Given coefficient instability in the selection stage and sensitivity across specifications, the bank-based ZINB results are interpreted cautiously. Nonetheless, the negative IPR intensity effect remains directionally consistent with the market-based results.

The venture capital specification (Table A.7) is estimated on a considerably smaller sample (358 observations in Column 4), reflecting the limited global coverage of VC data. Despite this constraint, the selection equation is remarkably stable: the coefficient on log GDP per capita is large, negative, and highly significant across all models (e.g., $\zeta = -5.502$, $p < 0.01$ in Column 4), indicating that even among relatively wealthy economies, incremental differences in income strongly stratify frontier participation.

In the intensity equation, IPR strength is again negative and statistically significant across all specifications. In the fully controlled model, $\zeta = -0.636$ ($p < 0.05$), implying that a one-unit increase in IPR strength reduces expected breakthrough intensity by approximately $e^{-0.636} - 1 \approx -47\%$ at mean VC depth.

The interaction between VC depth and IPR is positive and statistically significant across most specifications (e.g., $\zeta = 0.358$, $p < 0.10$ in Column 4). While deeper venture capital markets partially mitigate the negative association between strict patent protection and breakthrough intensity, they do not eliminate it at observed levels of VC depth.

Importantly, the negative IPR coefficient remains stable across all financial channels and specifications in the intensity equation. This consistency strengthens the quality-related TWFE results: stricter patent protection may increase overall patenting activity, but it is associated with a reduction in frontier-level breakthrough innovation.

6 Summary and Final Thoughts

The intention of this thesis was to identify the institutional and financial environments most conducive to high quality patents... *not just more patents*. Using two complementary empirical strategies, I document a consistent pattern across countries and time. Stronger patent protection is associated with increased patenting intensity, particularly in financially developed systems. However, the same institutional strengthening is associated with weaker innovation quality and reduced breakthrough intensity in financially mature environments. In other words, financial deepening and strict IPR regimes appear to expand the volume of patenting while diluting its average quality.

The interaction between financial structure and patent protection is central. Market-based systems amplify patent proliferation under strong IPR, while simultaneously exhibiting diminishing, and often negative, marginal returns to quality and breakthrough innovation. In the frontier models, Venture Capital partially mitigates this effect but does not overturn the negative association between strict IPR and breakthrough intensity. Across specifications in the count models, the negative IPR coefficient remains most compelling.

These findings should be interpreted with appropriate caution. Data availability limits coverage, resulting in sample contraction and compositional shifts. The ZINB models rely on cross-sectional variation rather than within-country identification. Still, the main patterns remain robust across methods and financial channels, and may inform our policy design related to intellectual property rights (if quality is the goal).

Future research could exploit the underlying micro-level patent data (rather than the country aggregates I constructed) to examine firm-level responses to institutional and financial environments.

Such analysis would allow for stronger causal identification and a deeper understanding of how institutions shape the direction and scale of technological change.

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):

$$\ln(\mu_{it}) = \zeta_0 + \zeta_1 FD^c_{it} + \zeta_2 IPR^c_{it} + \zeta_3 (FD^c_{it} \times IPR^c_{it}) + \mathbf{X}'_{it}\zeta + \ln(\text{Patents}_{it}) \tag{3}$$

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)	1981	29	4.22	1.61	0.11	4.39	8.19
Market Finance (log)	1742	37	-0.00	1.06	-3.74	0.03	3.73
Bank Finance (log)	1746	37	0.00	0.67	-2.16	0.06	1.50
Venture Capital (log)	637	77	-0.00	0.98	-1.52	-0.14	4.65
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: Bank Finance and Patent Quality

	Dependent variable:				
	Average Patent Quality (0–100)				
	(1)	(2)	(3)	(4)	(5)
ln(Bank Credit/GDP)^c	-1.162^{*}	-0.989	-0.910	0.213	-0.397
	(0.705)	(0.752)	(0.710)	(0.766)	(0.884)
IPR Strength^c	0.735	0.815	0.828	0.351	0.620
	(1.128)	(0.778)	(0.751)	(0.619)	(0.656)
Bank^c $\times$ IPR^c	0.481	0.446	0.648	-1.236^{**}	-0.722
	(0.888)	(0.834)	(0.915)	(0.538)	(0.698)
ln(GDP per Capita)		-0.693	-0.988	-1.668	-1.655
		(2.532)	(2.356)	(1.089)	(1.021)
ln(Trade Openness)			3.016	-0.447	-1.335
			(1.946)	(1.236)	(1.526)
ln(R&D Expenditure)				1.487	2.405
				(1.412)	(1.894)
ln(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
Note:	*p<0.1; **p<0.05; ***p<0.01				
	Country & Year FE included. Clustered SE in parentheses.				

Table A.3: Venture Capital and Patent Quality

	Dependent variable:				
	Average Patent Quality (0–100)				
	(1)	(2)	(3)	(4)	(5)
ln(VC Investment/GDP)^c	−0.517	−0.388	−0.354	−0.404	−0.259
	(0.550)	(0.529)	(0.522)	(0.608)	(0.712)
IPR Strength^c	0.079	0.091	0.106	0.221	0.599
	(0.806)	(0.786)	(0.777)	(0.954)	(0.965)
VC^c × IPR^c	0.071	−0.087	−0.119	−0.088	−0.059
	(0.701)	(0.723)	(0.754)	(0.849)	(0.828)
ln(GDP per Capita)		−1.810	−1.844	−1.986	−3.793
		(2.292)	(2.269)	(2.222)	(2.862)
ln(Trade Openness)			0.401	−0.118	0.953
			(1.975)	(2.050)	(2.306)
ln(R&D Expenditure)				1.191	0.718
				(1.702)	(2.089)
ln(Tertiary Education)					−3.656
					(2.236)
Observations	428	428	428	408	358
R^2	0.005	0.008	0.008	0.009	0.024
Note:	*p<0.1; **p<0.05; ***p<0.01				
	Country & Year FE included. Clustered SE in parentheses.				
	Continuous variables log-transformed + 1; FD, IPR mean-centered				

Table A.4: Market Finance and Patent Quantity

	Dependent variable:				
	ln(Patents per Capita)				
	(1)	(2)	(3)	(4)	(5)
ln(Market Cap/GDP)^c	0.095	−0.070	−0.085	−0.135*	0.011
	(0.096)	(0.081)	(0.079)	(0.081)	(0.110)
IPR Strength^c	0.491***	0.158	0.153	0.109	0.086
	(0.177)	(0.124)	(0.121)	(0.118)	(0.161)
Market^c × IPR^c	0.194**	0.132**	0.133**	0.180***	0.174**
	(0.079)	(0.062)	(0.062)	(0.046)	(0.069)
ln(GDP per Capita)		2.419***	2.460***	1.360***	0.771**
		(0.545)	(0.550)	(0.491)	(0.374)
ln(Trade Openness)			0.208	−0.021	−0.312
			(0.216)	(0.238)	(0.267)
ln(R&D Expenditure)				1.053*	0.756*
				(0.606)	(0.458)
ln(Tertiary Education)					0.929***
					(0.249)
Observations	1,334	1,329	1,329	841	598
R^2	0.096	0.355	0.357	0.210	0.385

Note: *p<0.1; **p<0.05; ***p<0.01
Country & Year FE included. Clustered SE in parentheses.
Continuous variables log-transformed + 1; FD, IPR mean-centered

Table A.5: Venture Capital and Patent Quantity

	Dependent variable:				
	ln(Patents per Capita)				
	(1)	(2)	(3)	(4)	(5)
ln(VC Investment/GDP)^c	−0.077	−0.098	−0.054	−0.030	0.062
	(0.095)	(0.081)	(0.082)	(0.077)	(0.067)
IPR Strength^c	−0.172	−0.193	−0.191	−0.249	−0.239
	(0.167)	(0.153)	(0.158)	(0.183)	(0.174)
VC^c × IPR^c	0.022	0.046	0.003	−0.030	−0.082
	(0.103)	(0.097)	(0.102)	(0.108)	(0.087)
ln(GDP per Capita)		0.386	0.405	0.457*	0.764***
		(0.329)	(0.311)	(0.255)	(0.288)
ln(Trade Openness)			0.497*	0.519	0.320
			(0.287)	(0.324)	(0.268)
ln(R&D Expenditure)				−0.093	0.170
				(0.453)	(0.366)
ln(Tertiary Education)					0.267
					(0.248)
Observations	418	418	418	398	348
R^2	0.025	0.035	0.064	0.070	0.106

Note: *p<0.1; **p<0.05; ***p<0.01
Country & Year FE included. Clustered SE in parentheses.
Continuous variables log-transformed + 1; FD, IPR mean-centered

Table A.6: 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.7: 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

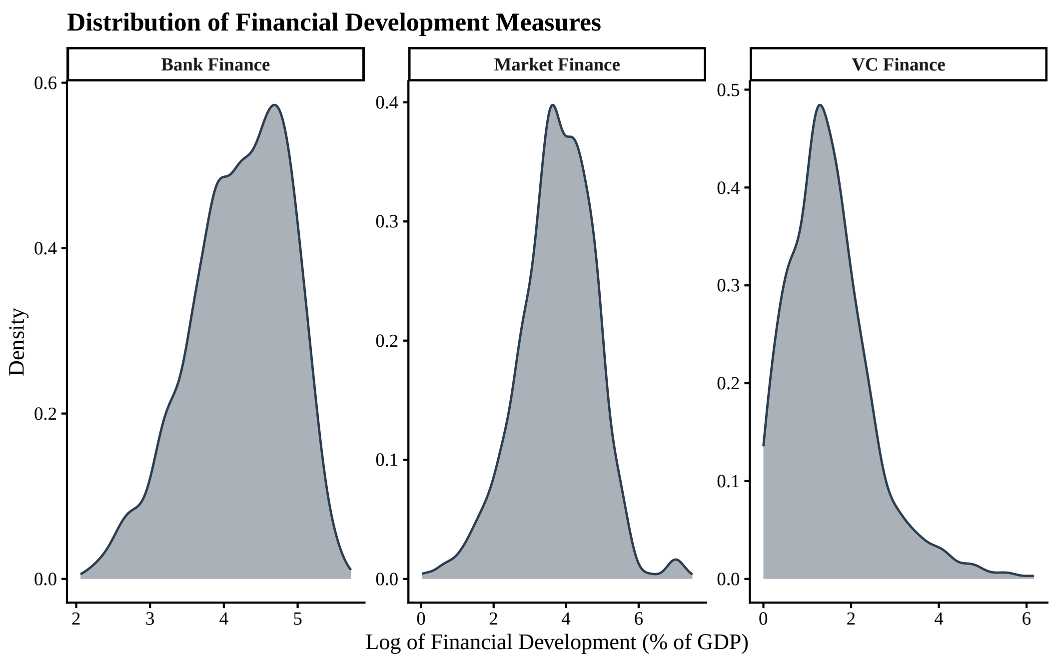

Figure A.1: Financial Development Distributions

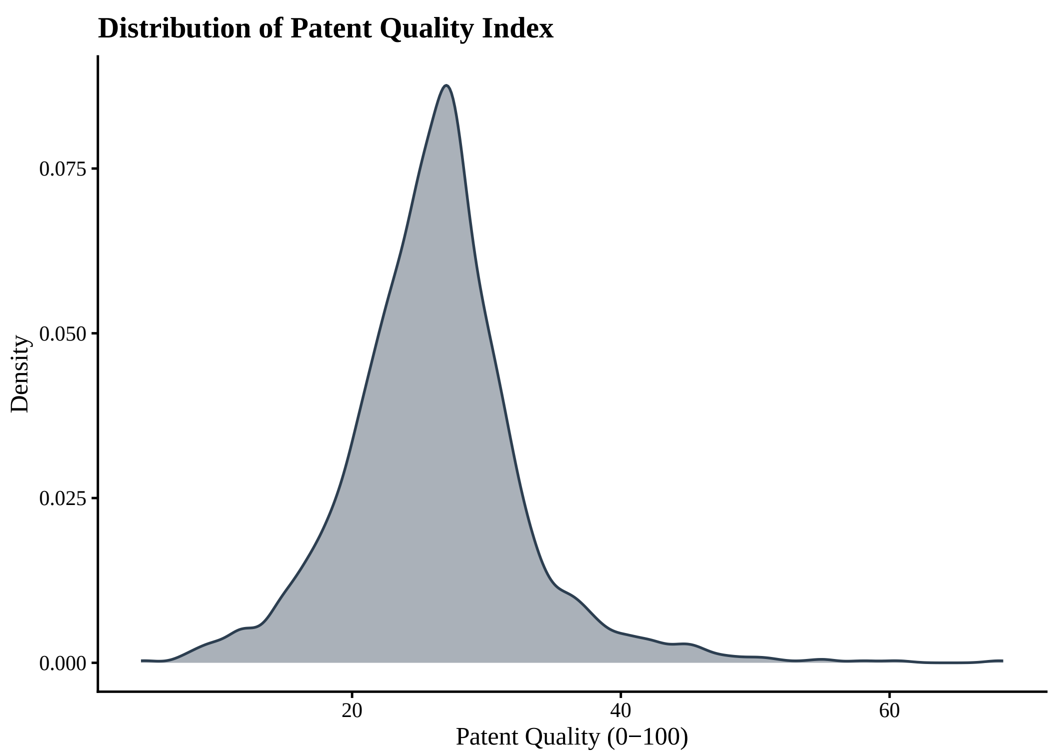

Figure A.2: Patent Quality Density by Variable

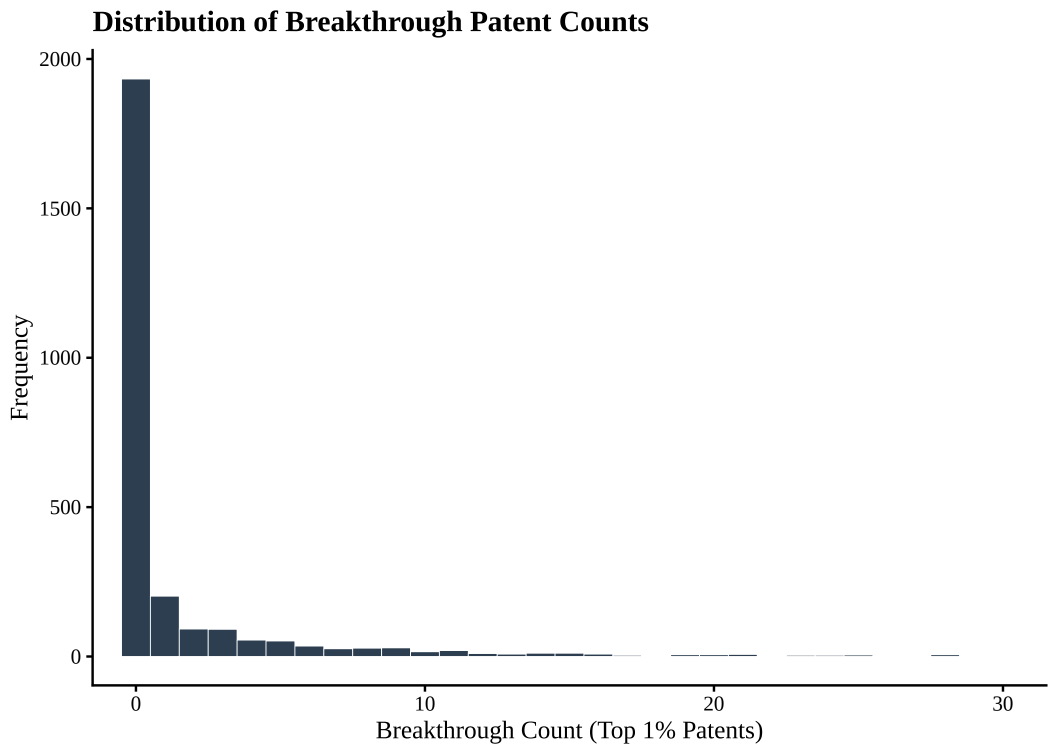

Figure A.3: Breakthrough Patent Distribution

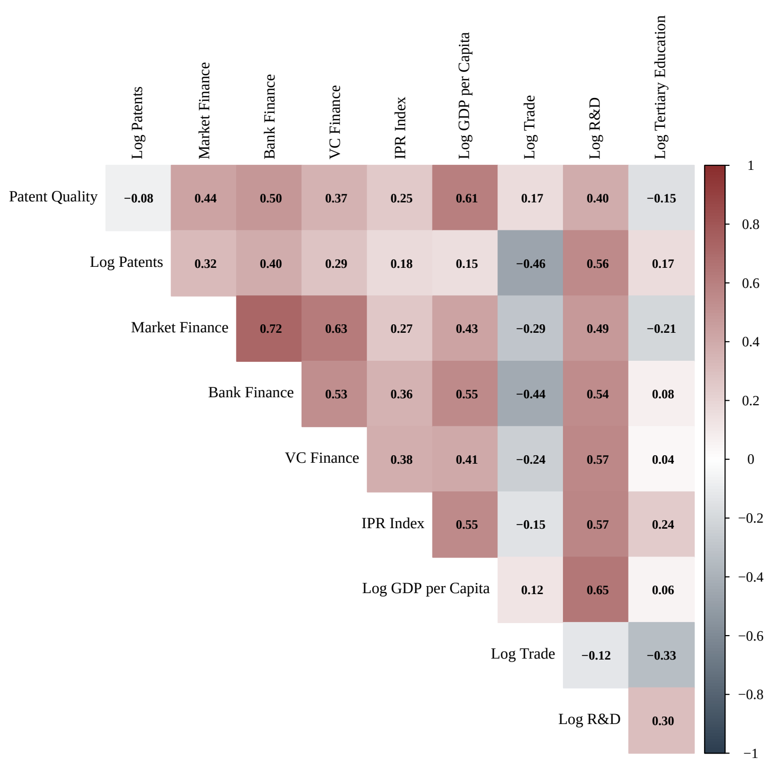

Figure A.4: Correlation Matrix of Key Variables

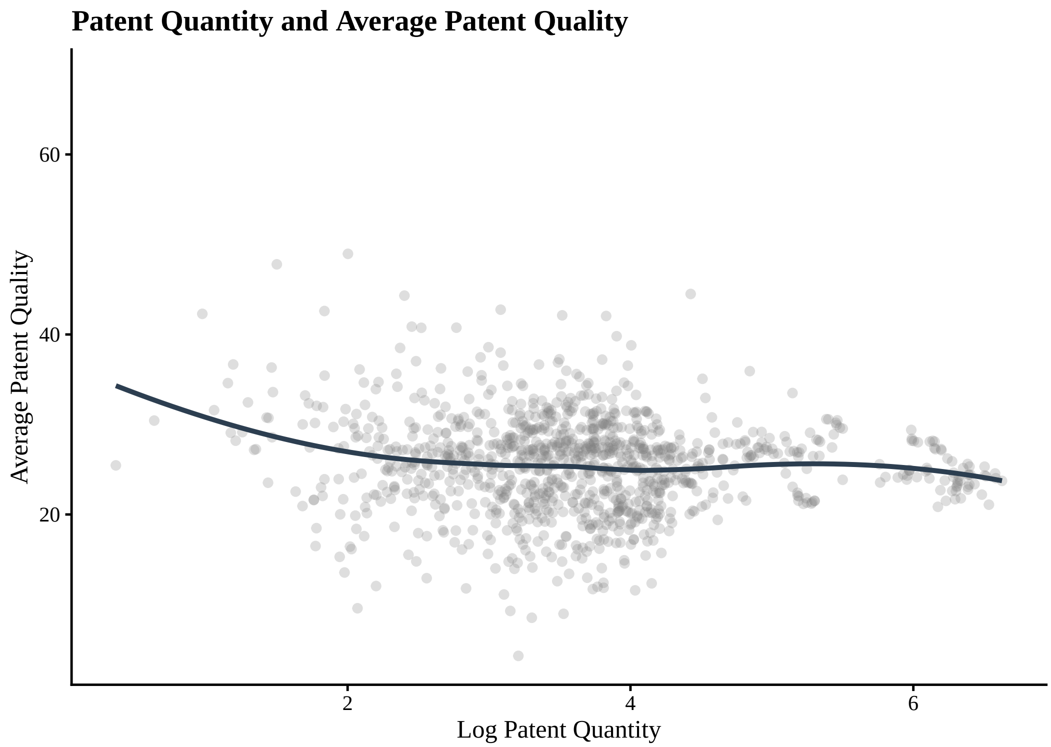

Figure A.5: Patent Quality vs. Patent Quantity

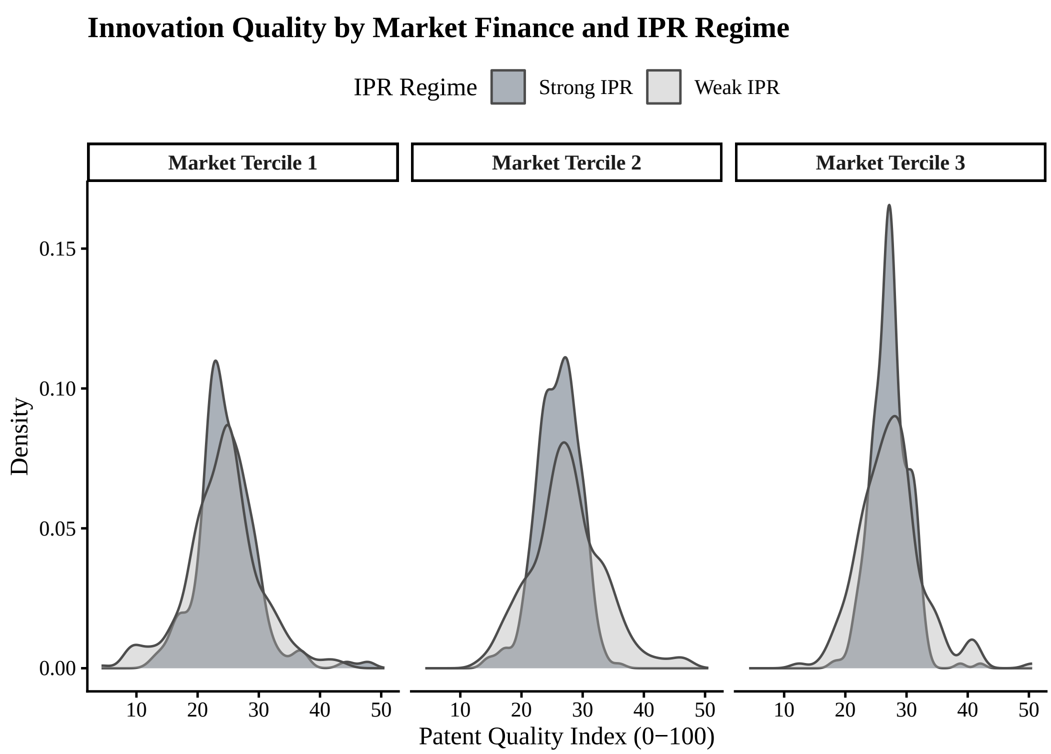

Figure A.6: Innovation Quality by Financial Regime

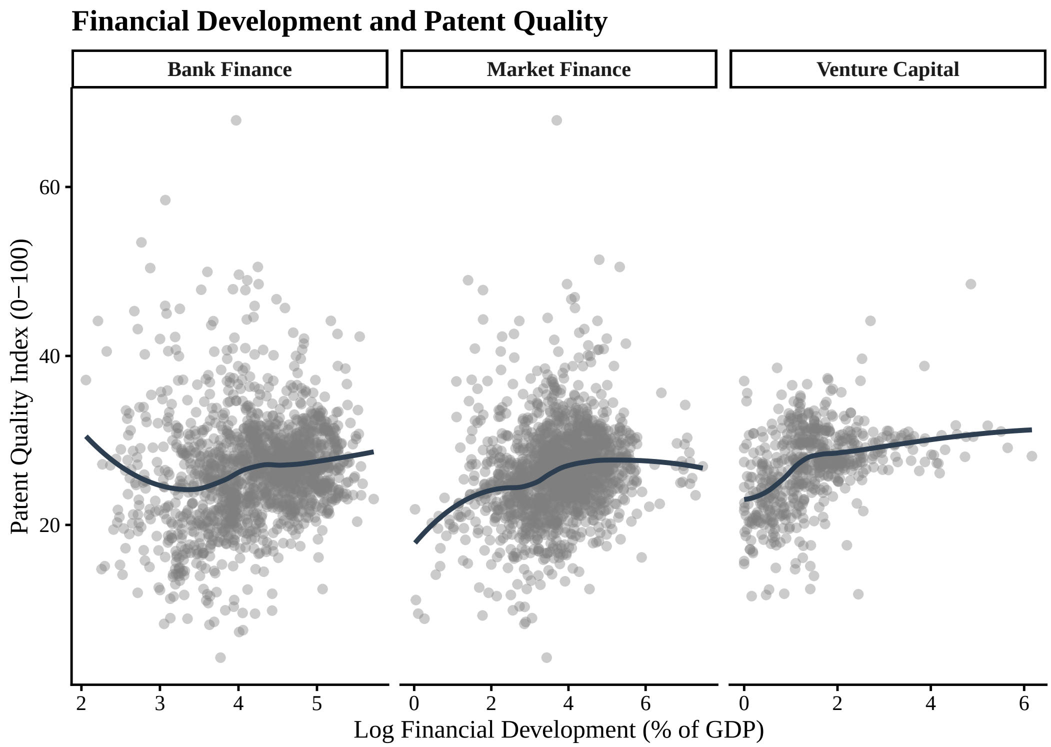

Figure A.7: Scatter: Financial Development and Quality

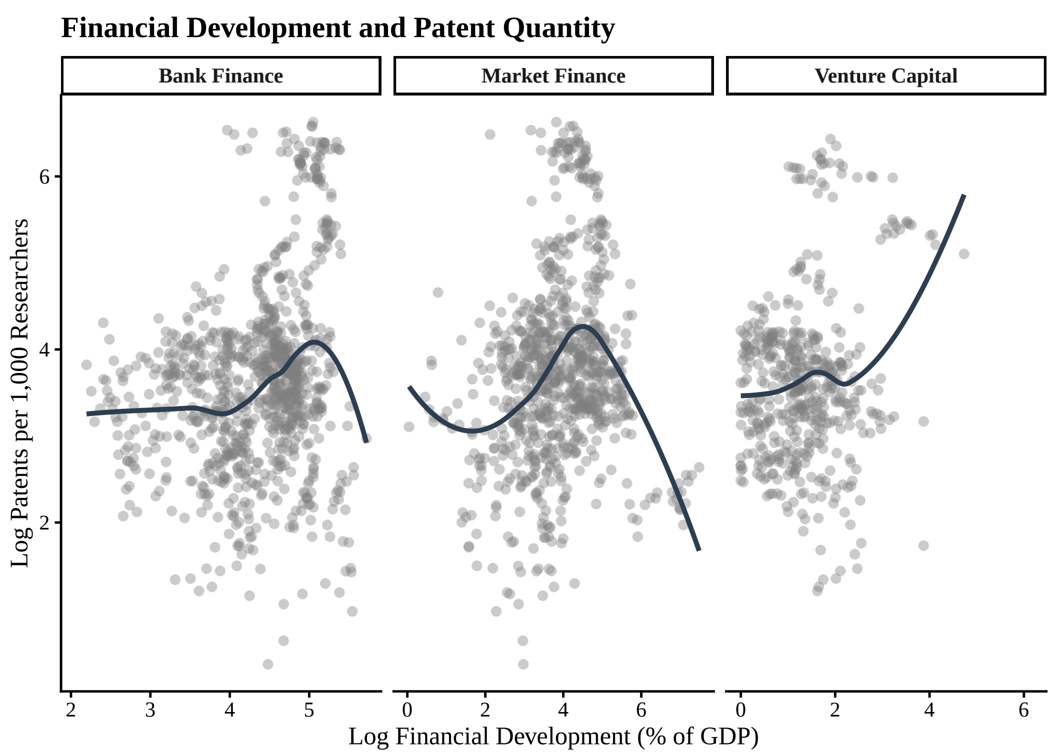

Figure A.8: Scatter: Financial Development and Quantity

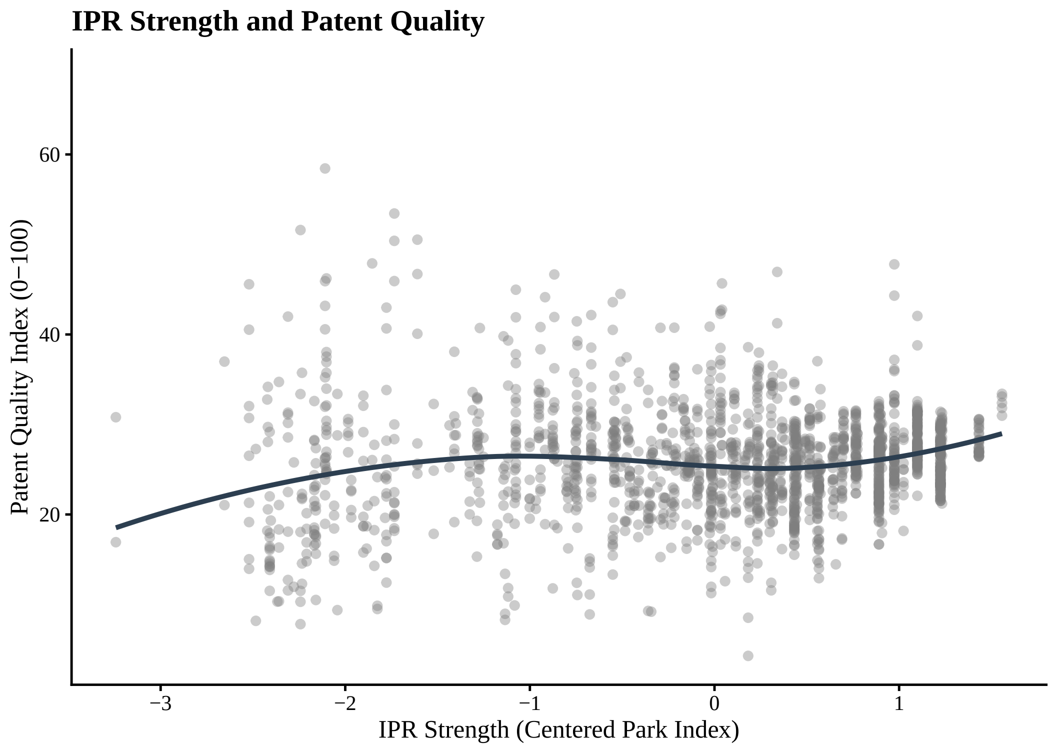

Figure A.9: Scatter: IPR Strength and Quality

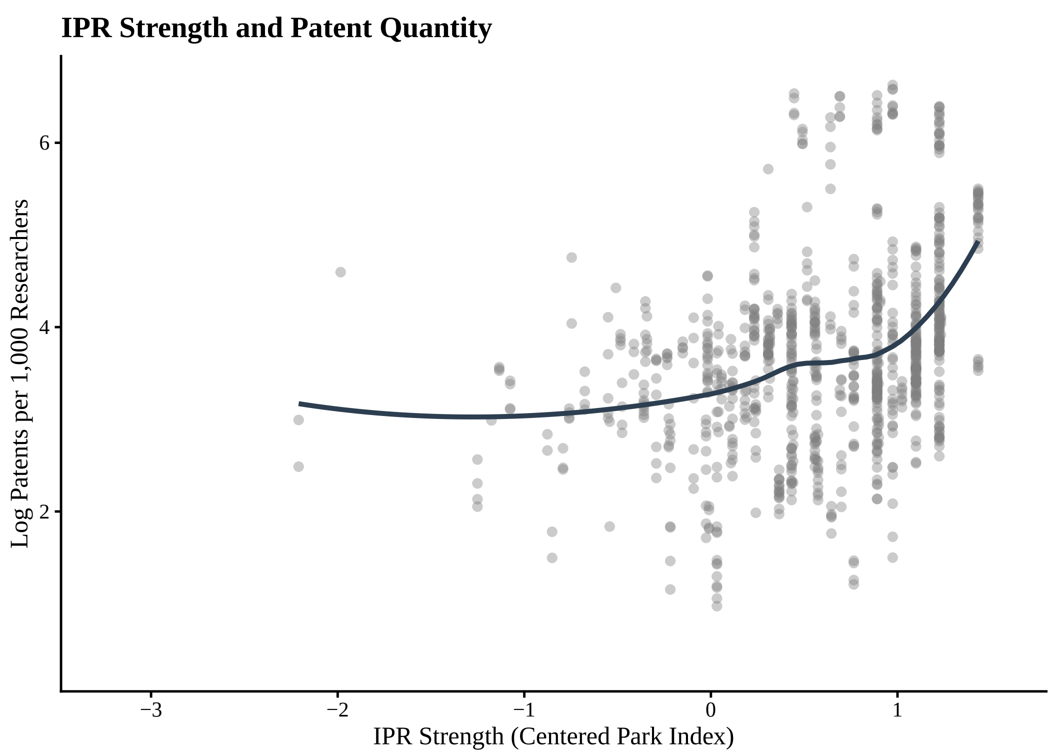

Figure A.10: Scatter: IPR Strength and Quantity

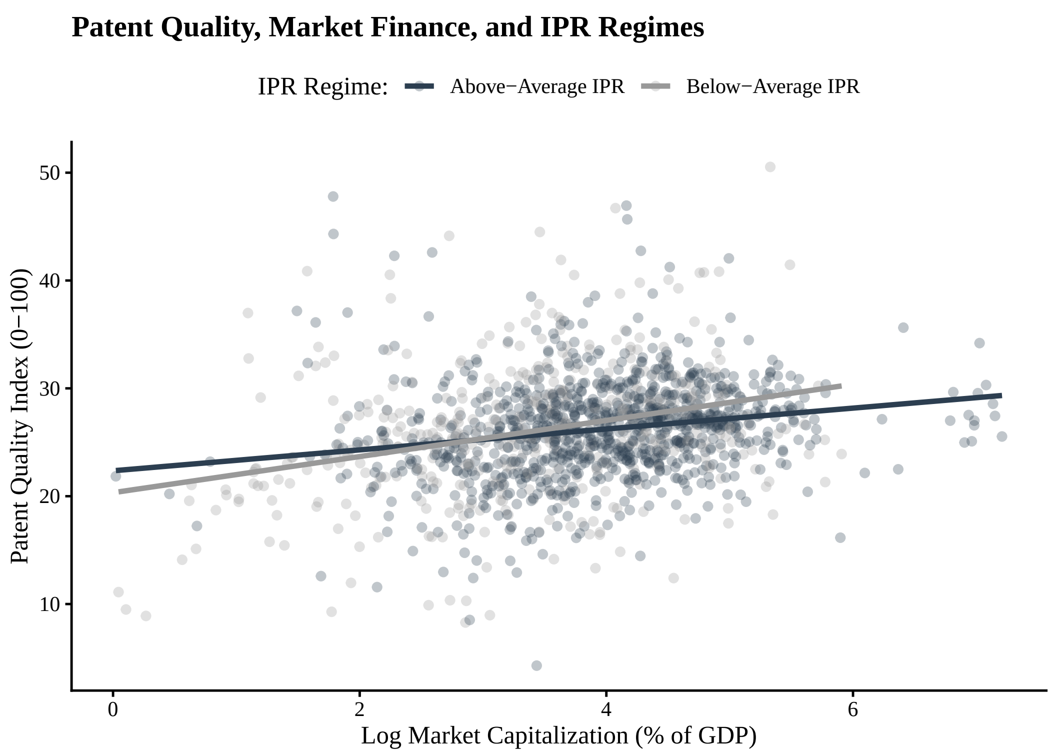

Figure A.11: Binned Interaction Scatterplot

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

Mikhail Bakunin

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