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Determinants of innovation outcomes: The role of institutional quality

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ABSTRACT

This paper uses unconditional quantile regression analysis to interrogate the effects of institutional quality on innovation outcomes. We assess important determinants of innovation such as property rights (including enforcement of intellectual property rights), human resources within R&D and high-technology exports. Regarding intellectual property rights, while most previous research focuses on patent strength (*de jure* or book law), we focus on *de facto* patent enforcement. Using data from the World Bank, the Heritage Foundation and a new patent enforcement index, we construct a panel of fifty countries covering 1998–2017. Our analysis reveals important new insights including the strongly negative impact of patent enforcement and human resources within R&D on less innovative economies, and the varying impacts across quantiles for key variables such as high-technology exports. We find that both stronger institutions and patent enforcement are not necessarily the best route to boosting innovation, especially in economies where existing innovative capacity is weak

1. Introduction

Innovation is considered a central driver of economic development and the growth and competitiveness of firms and nations (Schumpeter, 1911; Romer, 1986, 1990; Solow, 1956). Unsurprisingly, scholars have expended considerable energy seeking to identify the conditions most conducive to innovation. A key insight from this literature is that the institutional configurations favourable to innovation are contingent on a range of factors including the country's level of economic development and its level of innovative capacity (Hudson and Minea, 2013; Anand et al., 2021). In this paper, we apply Unconditional Quantile Regression (UQR) analysis to understand how strong predictors of institutional quality identified by previous research (for summaries, see He and Tian (2020); Neves et al. (2021)), vary across the distribution of innovation outcomes rather than only the mean, as is done conventionally (see Becheikh et al. (2006)).

During the last decade, there has been a significant increase in academic research devoted to examining the relationship between institutions and innovation (He and Tian, 2020). Although there is a growing emphasis on 'soft' or informal institutions including social mores (Donges et al., 2021; Adhikari and Agrawal, 2016) and corporate culture (Sunder et al., 2017), the majority of studies continue to focus on formal economic and political institutions (Acemoglu and Robinson, 2012) including the development of finance and product markets (Moshirian et al., 2021), human resource endowments (Cinnirella and Streb, 2017; Anelli et al., 2020), government policies, regulations and laws, including industrial policy(Cheah and Ho, 2020), competition policy (Anderson et al., 2021), fiscal incentives (Mukherjee et al., 2017), trade policy (Akcigit et al., 2018), and, most notably, the protection of property rights in general and intellectual property rights (IPR) in particular. Indeed, the relationship between the strength of IPR systems and innovation outcomes remains controversial (Sweet and Eterovic, 2019; Woo et al., 2015; Neves et al., 2021). This issue is exacerbated by the reliance of most previous studies on indices (see, for example, Ginarte and Park (1997); Park (2008)) or empirical models employing count data variables such as laws and reforms relating to IPR systems (Allred and Park, 2007; Chen and Puttitanun, 2005; Kanwar and Evenson, 2003). These approaches offer only a partial understanding of the effectiveness of IPR systems because they assume the existence of a strong set of laws to be a necessary and sufficient condition to protect property rights. In reality, the potency of IPR regimes are frequently compromised by patchy enforcement (Maskus, 2014), something that this paper aims to address by explicitly including a measure of IPR enforcement for a panel of countries over time.

Using data from the World Bank Development Indicators 2019, the World Bank Financial Structure Database 2019 and the Heritage

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Foundation's Index of Economic Freedom (2020) along with Papageorgiadis and Sofka's (2020) recently expanded patent enforcement index (henceforth the JWB, 2020 index or *JWBI*), we employ panel data for fifty countries spanning the period from 1998 to 2017 to analyse how institutional quality affects innovation outcomes. Conventionally, research in this area employs mean-based models such as ordinary least squares (OLS) regression analysis (see Becheikh et al. (2006)) as well as panel methods which estimate the impact of institutional arrangements and patent enforcement on average innovation levels. The novelty of our research design lies in the application of unconditional quantile regression (UQR) (Firpo et al., 2009) methods to gain better understanding of the impacts of key variables of interest on the *distribution* of innovation outcomes. To the best of our knowledge this is the first paper to apply UQR to analyse determinants of innovation outcomes for a panel of countries.

The paper makes three contributions to the literature. By using UQR methods our analysis, firstly, reveals subtleties and nuances in the drivers of innovation outcomes that means based methods overlook. Specifically, UQR enables us to detect how important variables such as researchers engaged in R&D and patent enforcement affect innovation outcomes across the entire distribution. For example, while our results show a strong positive relationship between both patent enforcement and higher proportions of researchers engaged in R&D to the right of the distribution of innovation outcomes (where stronger innovators are located), they also reveal a strongly negative relationship towards the left of the distribution where lower volumes of innovation takes place. Likewise, UQR reveals important differences in the *magnitude* of the impact of institutions on innovation outcomes. For instance, the impact of researchers engaged in R&D is almost four times stronger at the extreme right of the distribution ($\tau = 0.90$) as compared to the middle of the distribution ($\tau = 0.50$).

Second, we contribute to the literature by interrogating the impact of several predictors of institutional quality on innovation outcomes, going beyond the prevailing approaches that treat book law as a proxy for the quality of institutions and of IPR systems (Kanwar and Evenson, 2003; Kanwar, 2007; Akiyama and Furukawa, 2009; Furukawa, 2010). Although yielding important insights, a shortcoming of these approaches is that they may misspecify the relationship between innovation and IPR strength because they do not take into account whether IPR laws are evenly and effectively enforced (Maskus, 2014; Papageorgiadis and Sharma, 2016; Brander et al., 2017). To test the specific effects of patent enforcement on innovation we incorporate the JWB index within our model. Whereas the OLS model fails to detect any significant relationship between patent enforcement and innovation outcomes, UQR results show that the effect of patent enforcement varies between more and less innovative economies. Additionally, we find evidence of possible nonlinearities associated with patent enforcement. Our results bolster the accumulating evidence pointing towards an inverted U-shaped relationship between IPR and innovation, showing that there is not only an optimal level of IPR protection strength, but also an optimal level of IPR *enforcement*.

Third, we examine cross country evidence over a long period spanning two decades to analyse determinants of innovation outcomes. By using panel data for fifty countries from 1998 to 2017 the paper addresses geographical and temporal limitations from previous data sets, particularly by use of unconditional quantile methods which enable us to investigate relationships across the entire distribution, rather than focusing on the mean alone. This approach enables us to conduct robust empirical analysis and gain important insights into underlying relationships using our panel data.

2. Literature review

In the popular imagination, the notion of innovation conjures up images of white coated scientists and their 'euruka' moments which lead to the confinement of disruptive technologies that drastically transform business models, industries, economies and even ways of life. Radical innovations of this kind are, by their nature, unusual and, for the most part, the realities of innovation are more prosaic. Most innovations are incremental involving the development of goods and services with new or significantly improved characteristics (product innovation), new or significantly improved production or delivery methods (process innovation), new or significantly improved product packaging, placement, promotion or pricing (marketing innovation) or new working routines and practices (organizational innovation). Discussions of innovation likewise distinguish between those that are 'new to firm' (where a firm implements an improved product or process already implemented by others), 'new to market' (where a company brings an improved product to its market before its rivals), and 'new to the world' (where a firm is the first to implement the innovation for all industries worldwide (see (OECD, 2005). Innovation is therefore a multifacted and multiphased phenomenon. Irrespective, most definitions hew closely to the idea that innovation requires the invention and introduction to the market something which entails a degree of novelty. Innovation boosts the competitiveness of firms and the productivity of the national economies they inhabit, in turn catalysing a virtuous circle of higher wages, expenditure, investment and economic growth. Against this background, investigations to identify and understand drivers of innovation have become a major preoccupation of scholarly research. This research has trained its sights primarily on the determinants of innovation at firm level but to realise their full benefits, innovations must be diffused across the economy and country wide outcomes are therefore extremely important. Moreover, the tendency of innovative companies to cluster in specific locations has magnified interest in assessing the determinants of innovation at the national level (Rodríguez-Pose and Zhang, 2020).

When it comes to explaining cross-national differences in innovation performance, it is widely accepted that "institutions matter" (Rodríguez-Pose, 2013) (see also Acemoglu and Robinson (2012, 2006); Olson (1996); Peng et al. (2017a); Rodrik (2008); Rodríguez-Pose and Zhang (2020)), indeed, for some, "the *quality* of institutions trumps everything else (our emphasis)" (Rodrik et al., 2004, p. 131). The exact definition of an institution remains contested but most authors coalesce around the idea that institutions are

> "systems of established and prevalent social rules that structure social interactions" (Hodgson, 2006, p. 2).

Institutions may be formal (rules codified in written laws, constitutions, judicial decisions and contracts) or informal (conventions and codes of behaviour founded on customs, norms and tradition). Irrespective, institutions, to borrow North's (1990: 1) phrase, "constitute the rules of the game" that constrain or enable economic interactions. Institutions are critical for innovation because they lower transaction costs arising from information asymmetry, bargaining and coordination and enforcement of contracts (North, 1990). By limiting opportunism through a system of incentives and disincentives, thereby creating stable expectations about the behaviour of counterparties, institutions help economic agents to mitigate the uncertainties and externalities of their activities (Alonso and Garcimartín, 2013; Wu et al., 2015). There are nevertheless challenges in operationalising institutions as a variable, not least that "the measurement issue looms large (Jellema and Roland, 2011, p.108, p.108)". These problems are most pronounced for informal institutions, where quantifying the abstract and intangible reasoning underlying these relationships is all but impossible (Rodríguez-Pose, 2013). Even formal institutions, which in-keeping with the wider literature on institutions and innovation, are the main focus of this paper are not immune from these problems. For example, as we will discuss in more detail below, many laws related to IPR are routinely ignored or not enforced. As Hodgson (2006) points out, however, laws that are ignored have a tenuous claim to be 'rules' because they are not mediating social interactions by altering the incentives for certain kinds of behaviour. It is for this reason that this paper takes the effective enforcement rather than the mere existence of IPR laws as a proxy of institutional quality.

Drawing on the national systems of innovation (NSI) approach, numerous scholars have shown that the functioning of an innovation system is contingent on the quality of its supporting institutions (Edquist, 1997), focusing on institutions related to the quality of the scientific and technological system, prevailing IPR laws, public policies and educational aspects to explain differences on innovation outcomes across countries (Anand et al., 2021; Furman et al., 2002; Lundvall, 1992; Sun et al., 2021; Varsakelis, 2006). Also scholars from other related approaches argue that institutions are extremely important amongst country-level characteristics for analysing the determinants of innovation (Acemoglu and Robinson, 2012; Olson, 1996; Peng et al., 2017a; Rodrik, 2008; Rodríguez-Pose and Zhang, 2020). Studies have generally confirmed the expectation that firms located in countries with a high quality institutions characterised by a sound regulatory frameworks, effective legal processes, respect for the rule of law, strong enforcement of regulations and IPR, low levels of corruption and suitable policies, are more likely to invest in innovation activities and to have a better innovation performance (Blind, 2012; Fuentelsaz et al., 2018; Tebaldi and Elmslie, 2013). Moreover, in countries with high quality institutions, firms have better access to advanced technologies, knowledge, capabilities and other resources critical to the innovation process and to innovative performance (Almeida and Kogut, 1999; Fuentelsaz et al., 2018; Nelson, 1993; Hemmert, 2004; Wu et al., 2015). Despite the consensus that the quality of institutions matters, different authors have considered different types of institutions (using different proxies which are often indices of institutional quality), often in isolation. In this paper, four predictors of the quality of institutions are considered, associated with differences in innovation between countries: respect for property rights, patent enforcement, the endowments of human resources in R&D and the country's specialisation profile. While these predictors do not completely encompass all institutional dimensions, we contend that they include the most important components determining the quality of the institutional environment influencing innovation outcomes.

As one of the main market-creating institutions (Baumol et al., 2007), respect for property rights is considered a key pillar of institutional quality within national business environments (La Porta et al., 1999; Ayyagari et al., 2021). Acemoglu and Johnson (2005) stress two related aspects of property rights: the risk of expropriation by arbitrary government action and the quality of contracting institutions. Property rights are related to a country's allocative efficiency, ensuring that investors can retain the returns to their investments, which is considered a key principle for sound economic governance (Rodrik, 2008). Thus, firms' incentives to innovate depend on the ability to protect and exploit property rights arising from innovation (Angelopoulos et al., 2011). A robust system of property rights protection is also vital to ensuring the financial investments upon which innovative ventures rely (Fogel et al., 2008).

Few empirical studies detail the effects of property rights at country level. Nevertheless, they provide clear evidence relating to the importance of property rights to innovation outcomes. Countries with stronger rule of law and integrity of contracts consistently perform better across a range of economic indicators including innovation (Simón-Moya et al., 2014). By undermining entrepreneurial incentives, weaker rule of law, in terms of protection of property rights, is likely to impact negatively on innovation outcomes.

Among property rights, IPR in general and patents in particular, are regarded as a crucial institutional determinant of innovative behaviour and have been widely included in empirical studies (Teece, 2006; Kanwar and Evenson, 2003; Furukawa, 2010). As part of a broader IPR ecology, patents are essential for addressing market failures associated with the innovation process. Innovations are both non-rivalous and non-excludable. That is to say, the use of an innovation by one producer does not preclude its use, authorised or otherwise, by others (non-excludable) and the employment of an innovation does not leave a lower quantum of innovation available to others (non-rival). Consequently, the gains from innovation are difficult to appropriate and returns to investment, such as research and development (R&D) expenditures, become uncertain. This prompts firms to shelve innovative activity that may be socially desirable because it is privately unprofitable. A system of patents ameliorates these problems by conferring on the innovator the exclusive right, for a fixed period, to reap the economic rewards arising from the innovation. Therefore, it is conventional to postulate a positive monotonic relationship between the strength of IPR protection and innovation activity (Grossman and Lai, 2004, 2006), a hypothesis with plentiful empirical confirmation (Ang et al., 2014; Kanwar, 2007; Schneider, 2005). This mainly arises from longer duration of monopoly rights that patents typically confer. In this scenario, future profits have a greater discounted present value further incentivising innovative activity.

While it is generally accepted that some level of intellectual property protection is required to protect innovation related investments, it is also recognized that patents can negatively effect innovation outcomes (Sweet and Maggio, 2015; Woo et al., 2015). Granting patents may help to sustain a favourable climate for future innovation but at the cost to society of forgoing immediate access to the latest knowledge. The essence of this so-called 'patent-bargain' (Jensen et al., 2007) is that by disclosing their innovation, patent holders add to society's stock of knowledge which it can fully exploit once the property rights lapse. Nevertheless, by suppressing the free flow of information patents inhibit innovation. For example, patents increase transaction costs within markets by requiring subsequent innovators to license earlier technologies to conduct R&D (Sampath, 2007), thereby slowing cumulative and sequential innovation (Hopenhayn et al., 2006; Bessen, 2009; Horii and Iwaisako, 2007). Likewise, many patent filings are 'strategic' or 'defensive' whose intent is to preserve market share rather than to guarantee returns on economic exploitation of the innovation (Neuhäusler, 2012b; Walsh et al., 2016). Finally, patent systems slow the pace of innovation by hampering competition (Horowitz and Lai, 1996).

These contradictory effects call into question the existence of a linear relationship between IPR strength and innovation outcomes (Allred and Park, 2007; Hudson and Minea, 2013; Pathak et al., 2013; Sweet and Maggio, 2015). Proceeding from the premise that baseline safeguards are required to promote innovation but that excessive protection may blunt the incentive to innovate, more recent research examines the possible existence of an optimal level of IPR strength. Furukawa (2007, 2010) posits the existence of an inverted U-shaped relationship between IPR strength and innovation outcomes suggesting this non-monotonic relationship is the result of IPR protection that discourages innovation by suppressing learning by doing. In other words, both very weak and very strong IPR regimes lead to lower innovation. In a similar vein, Gangopadhyay and Mondal (2012) argue that given the imperfections of IPR regimes, knowledge spillovers from protected innovations are smaller than from those innovations that are not protected. The imposition of a very strict IPR regime would curb future innovation by inhibiting the knowledge accumulation process. They conclude that stricter IPR regimes do not necessarily lead to greater innovation or higher economic growth.

Using country level data, Hudson and Minea (2013) and Papageorgiadis and Sharma (2016) show that stronger IPR regimes tend to decrease innovation in countries starting with relatively low or relatively high initial IPR strength, but foster innovation within countries towards the middle of the distribution. Thus, for IPR protection higher than the optimal level, the positive effects for innovation are negated by the adverse effects in terms of costs and competition. Moreover, some studies suggest that the contours of the relationship may be affected by a country's level of development (Allred and Park, 2007; Maskus et al., 2019; Neves et al., 2021; Sweet and Maggio, 2015). Developing countries may have larger negative effects arising from stronger patent protections for innovation because they tend to introduce more incremental innovations and to perform adaptive R&D. A strict patent regime would hinder this type of innovation and could lead to slowing technological catch-up within these countries (Odagiri et al., 2010). In developing countries, governments often face a trade-off between facilitating the imitation of advanced technologies, usually imported from more advanced settings, and providing incentives for indigenous innovations (Chen and Puttitanun, 2005; Chu et al., 2014; Peng et al., 2017b).

Given the importance of IPR systems for innovation, governments need to develop intellectual property (IP) laws (i.e. book law or *de jure* aspect of the IPR system) and ensure their enforcement (the *de facto* aspect of the IPR system). Over the last two decades, there has been a tendency towards relative homogenisation between countries in terms of their IP laws (Chang et al., 2002), within the context of the World Trade Organisation (WTO) and the agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS). Significant differences remain, however, in terms of the effectiveness with which IP law is applied (Papageorgiadis and McDonald, 2019). Indeed concerns about weaknesses in IPR enforcement in emerging countries are at the heart of a host of contemporary trade disputes, most notably between the United States and China where the former alleges that the latter's stance on technology transfer thwarts the ability of foreign patent owners to enforce their patent rights (Peng et al., 2017b). As recent research stresses (Papageorgiadis et al., 2014; Papageorgiadis and McDonald, 2019), the existence of strict IP laws does not guarantee effective enforcement, which arguably better reflects the quality of institutions related to IPR protection as well as innovation outcomes which prevail.

Institutional quality is not limited to property rights, however. It is also related to the structural characteristics of a country's economy, as reflected in its organisation of production activities and specialisation patterns. In fact, development policies adopted across the world are an evidence of the role of public polices in fostering institutions that support technology upgrading and capacity building, contributing to increase the value-added of exports (Zhu and Fu, 2013). These specialisation patterns, built over time and influenced by public policy, affect the country's capacity to innovate and, therefore, the observed innovation outcomes (Frietsch et al., 2014; Mamede, 2017). This is particularly evident when we consider patents, since this innovation outcome is more frequent in some specific industries (Chen and Puttitanun, 2005; Mansfield, 1986) such as high technology sectors, and within some modes of innovation (Jensen et al., 2007). Therefore some scholars argue that specialisation patterns are created by comparative institutional advantages that shape the organizational competences necessary for innovation within particular technological domains (Casper et al., 1999; Hall and Soskice, 2001; Whitley, 2002). Previous research also shows that a country's productive structure, particularly the share of high technology sectors, co-evolves with the development of the scientific and technological infrastructure and the higher education system (Mamede, 2017). Thus, R&D's impact on innovation and economic growth depends significantly on the country's economic structure (Bilbao-Osorio and Rodríguez-Pose, 2004).

Reflecting the ability to compete in international markets based on technological and quality factors (Blind, 2012), exports are a widely used indicator of economic specialisation (Meelen et al., 2017). Specifically, high technology exports reflect technological capabilities and the country's economic and innovation history, being the result of a cumulative processes of learning (Lundvall, 1998) and of institutional factors (Anand et al., 2012). Furthermore, high-technology exports can be considered as a proxy for export complexity and technological sophistication, which is increasingly considered as an important determinant of a country's capacity for growth (Hidalgo et al., 2007; Hausmann et al., 2007). Countries specialised in low value-added and low-technology products face stronger international competition and are usually more focused on price competition and incremental innovations. Such countries often lack the necessary capabilities required to seize new opportunities presented by, and embodied within, scientific and technological breakthroughs.

The country's level of highly skilled human resources is also a strong predictor of institutional quality (Furman et al., 2002; Glaeser et al., 2004). Well educated people are necessary for the proper functioning of the judicial system and to solve disputes and commercial conflicts using institutional mechanisms (Glaeser et al., 2004); educated people also request, and contribute to the building of, more transparent and dynamic institutions (Alonso and Garcimartín, 2013). The NSI literature stresses its relevance as an institutional factor that contributes to increase innovation (Lundvall, 1992; Lundvall et al., 2002; Varsakelis, 2006). Endowments of highly educated and skilled people are necessary for establishing the infrastructure necessary for enhanced production as well as greater innovation (Dakhli and De Clercq, 2004) and there is plenty of evidence for the importance of highly skilled human resources for economic growth (Barro, 1991; Romer, 1990). Without highly skilled labor, especially scientists and engineers, it is unlikely that a country could produce cutting-edge technologies (Furman et al., 2002).

R&D represents an investment, or a significant input, into the innovation process. It also builds absorptive capacity that enables the use of external knowledge and the capacity to take advantage of knowledge spillovers (Cohen and Levinthal, 1990; Nelson and Phelps, 1966). Personnel employed in R&D tend to be highly qualified possessing advanced levels of education, often holding PhD degrees (Roach and Sauermann, 2010). Operating at the frontiers of science and technology (Cockburn and Henderson, 1998), R&D workers are repositories of skills and expertise (Nonaka and Takeuchi, 1995), but also holders of important tacit knowledge. Recent research regards the number of R&D employees as a good measure of absorptive capacity (Huang et al., 2015), which is vital to build capacities to recognise, assimilate, exploit, explore, transform and acquire external knowledge. R&D workers and their capabilities are crucial for the success of the R&D process, which ultimately enables the realisation of inventions and innovations (Herrera, 2020; Maggitti et al., 2013; Neuhäusler, 2012b; Salter et al., 2015). Indeed R&D workers are responsible for a high share of patent applications filled by the firms that employ them (Sauermann and Cohen, 2010).

This paper contributes to the extant research by focusing on institutional quality as a key determinant of innovation outcomes at country level. Adopting the theoretical framework outlined in Fig. 1, we employ an explanatory model that includes several predictors of institutional quality such as rule of law as embodied within protection of property rights, enforcement of IPR, patterns of specialisation as captured by high technology exports and human capital endowments in terms of research personnel engaged in R&D. Our model also includes a set of control variables widely used in previous research and for which there is already a broad consensus on their association with innovation outcomes at country level. These include: i) gross domestic product (GDP) per capita which measures purchasing power (Allred and Park, 2007); ii) population as a proxy for market size (Sweet and Maggio, 2015); iii) openness which signals the ease of exchange of ideas and technology (Chen and Puttitanun, 2005; Porter and Stern, 2000; Varsakelis, 2001); iv) foreign direct investment (FDI) which provides measures of availability of resources/funding and also enhances the possibilities for technology transfer (Grossman and Helpman, 1995; Hudson and Minea, 2013); and v) health expenditures as a proxy for the provision of public goods (Allred and Park, 2007).

3. Methodology

Our strategy follows the pragmatic approach set out by Kanwar and Evenson (2003), which continues to apply to empirical analysis in this area:

> one cannot afford to be doctrinaire about the model selection procedure adopted, for the simple reason that theory is just not well-defined enough to guide us in starting from the complete model. More often than not, the available data may be the binding constraint (p. 259).

We begin our analysis by making use of a standard multivariate

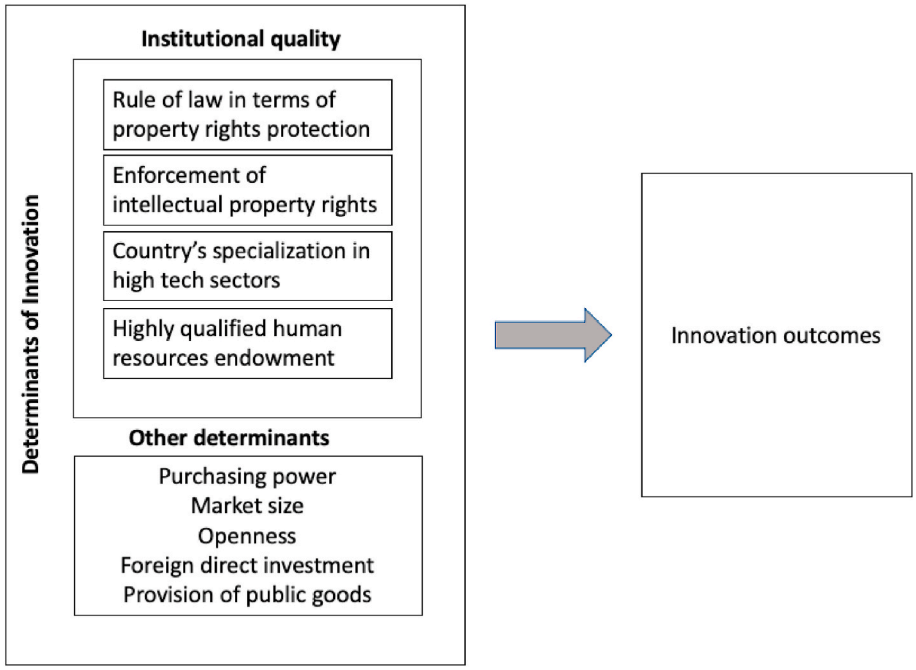

Fig. 1. Theoretical framework.

regression model, followed by estimates using panel fixed effects and random effects models (Wooldridge, 2010), which are our baseline case. These results are provided for purposes of comparison with subsequent unconditional quantile regression results. An established model used widely in the literature (Kanwar and Evenson, 2003; Kanwar, 2007; Hudson and Minea, 2013; Sweet and Maggio, 2015) which we adapt for our analysis takes the following specification:

$$\ln P_{it} = \beta_0 + \beta_1 \ln IPRI_{it} + \beta_2 \Omega_{it} + \epsilon_{it} \tag{1}$$

where $IPRI_{it}$ is a suitable IPR index which in our case is an index of patent enforcement (JWB, 2020 index), Ω_{it} is a vector of suitable covariates or control variables that explain innovation outcomes, as captured by number of patents P_{it}. Equation (1) can be modified to include squared terms of the patent enforcement index captured by *IPRI* in order to allow for nonlinearities and to enable us to relax the monotonicity assumptions as outlined in Furukawa (2010) and Sweet and Maggio (2015).

Following Koenker and Bassett (1978) quantile regression analysis has been widely employed within economics, finance and management. In the presence of well behaved data and normally distributed errors, means based estimation such as OLS are suitable and appropriate for use. However, OLS methods are less reliable when we face outliers or when mean based estimates contain insufficient information about the data. When the normality assumption fails to hold, OLS regressions become unreliable for the purposes of statistical inference. In contrast, Koenker type quantile regression models conventionally assume that the dependent variable is both independently distributed and homoscedastic providing a robust approach even when outliers are present and in the face of issues such as non-normal errors, possible non-linearities and potentially censored data, making them useful for a number of applied research contexts.

In Koenker and Bassett (1978) type quantile regression models, when the median is our quantile of interest we can achieve optimisation by minimising the sum of absolute value of residuals. In contrast to classical linear regression modelling, we achieve optimisation by minimising the sum of squared residuals. We can generalise the procedure for optimisation for a particular quantile of interest (say τ) as follows:

$$\min_{\beta \in \mathbb{R}} \left[\sum_{t \in (t: y \geq x_t \beta)} \tau |y_t - x_t \beta_\tau| + \sum_{t \in (t: y < x_t \beta)} (1-\tau)|y_t - x_t \beta_\tau| \right] \tag{2}$$

where $y_t - \beta x_t$ represents the residual from the regression of the vector of covariates, x_t, on the explanatory variable y_t. Despite their widespread use, the quantile regression (QR) methodology faces significant limitations. Specifically the parameters estimated and the impact of the explanatory variables on a quantile of the dependent variable are conditional upon the distribution of other covariates, hence this method is sometimes referred to as conditional quantile regression (CQR). As the values of the covariates change, so do parameter values contributing to parameter inconstancy and difficulties in interpreting and generalising empirical results, particularly in relation to relevant policy issues.

To address these limitations, we employ UQR (Firpo et al., 2009). UQR overcomes limitations of Koenker style quantile regressions by ensuring that the effect of an independent variable on the dependent or response variable is contingent only on the distribution of the dependent variable and not the distribution of the other covariates. Firpo et al. (2009) propose the estimation of a recentered influence function (*RIF*) which is constructed without reference to the other covariates. This recentered influence function is regressed on the explanatory variables in the second step of the UQR methodology. Assume Y represents the outcome of interest to us (total number of patents) and $F_Y(y)$ shows the population (unconditional) distribution function of Y within a target population. In other words $F_Y(y) = Pr(Y \leq y)$. We are chiefly interested in understanding the effect of a particular covariate (say X) on Y. We can express the RIF as follows (Firpo et al., 2009; Borah and Basu, 2013):

$$RIF(y, \mu) = \mu(F) + IF(y, \mu) \tag{3}$$

where F is the cumulative distribution function of the response variable y and μF represents the value of the statistic. In our analysis this corresponds to the logarithm of total patents. An attractive property of the *RIF* is that its expectation is simply equal to μF. We can thus define the influence function *IF*, where F represents the cumulative density function of Y and δ_y represents a distribution which only puts mass as value y, as follows:

$$IF(y, \mu(F)) = \lim_{\Phi \to 0} \frac{[\mu((\Phi)F + \Phi\delta_y) - \mu(F)]}{\Phi} \quad (4)$$

The equation above enables us to estimate RIF values which are subsequently employed in a further regression on the covariates. This method is particularly convenient and appealing within applied research because the *RIF* can be estimated using OLS for each quantile of interest. For our analysis, we estimate the RIF function from the 10^{th} to the 90^{th} quantile (τ) of the distribution. We employ bootstrapped standard errors to enhance the robustness of our results.

Assuming that the statistic of interest lies within a given quantile τ of the distribution of the outcome variable (in our case total patents), we have (see also Borah and Basu (2013):

$$IF(y, q_\tau) = (\tau - \Lambda\{Y \le q_\tau\})/f_Y(q_\tau) \quad (5)$$

where q_τ denotes the τth quantile of the unconditional distribution of Y, $f_Y(q_\tau)$ represents the probability density function of Y evaluated at q_τ, while $\Lambda\{Y \le q_\tau\})$ represents an indicator variable to show whether the value of the outcome variable is less than q_τ or not. Consequently, we have:

$$RIF(y, q_\tau) = q_\tau + IF(y, q_\tau) \quad (6)$$

Firpo et al. (2009) demonstrate that when the conditional expectation of $RIF(y, q_\tau)$ is modelled as a function of explanatory variables, the resulting *RIF* regression can be straightforwardly regarded as an example of an unconditional quantile regression. Given a particular quantile τ the first step involves an estimation of *RIF* at the τth quantile of Y. We estimate q_τ using the sample estimate of the unconditional τth quantile. We estimate the density $f_Y(q_\tau)$ at the point q_τ by employing kernel or other methods (Firpo et al., 2009). In the second step, an ordinary least squares regression of the $RIF(y, q_\tau)$ is run on the vector of covariates Ω.

4. Empirical analysis

4.1. Data and variables

We analyse determinants of innovation outcomes with particular focus on the role of predictors of institutional quality using data for a panel of fifty countries between the years 1998 and 2017 (see Table 1 for countries within our sample). Our study employs data obtained from the World Bank Development Indicators 2019, the World Bank Financial Structure Database 2019, the Heritage Foundation's Index of Economic Freedom (2020) and a recently developed index of patent enforcement (Papageorgiadis and Sofka, 2020). Our chosen variables are defined in Table 2.

As is conventional in panel studies our dependent variable for innovation outcomes is the natural logarithm of total patents for each country ((Chen and Puttitanun, 2005; Gamba, 2017; Hudson and Minea, 2013; Kim et al., 2012; Varsakelis, 2006; Yang et al., 2014) Qiu and Yu (2010)). Our patent data variable is obtained from the World Bank's *World Development Indicators* (WDI) which source this data from the World Intellectual Property Organisation's (WIPO) *WIPO Patent Report: Statistics on Worldwide Patent Activity*. Patent applications recorded in this database include international patent applications filed in compliance with Patent Cooperation Treaty procedure or with respective national patent offices for gaining exclusive rights for an invention including both a product or a process that creates a new way of doing something or offers a new technical solution to a specific problem. Patent protection is granted the owner of a patent for a limited period of time, normally twenty years. We therefore use this WDI data for measuring innovation based on patent applications filed for each country. Although patents so recorded do not fully reflect the innovation activities of every country, we believe this measure of innovation (as measured by patents granted) is a valid and useful proxy measure of innovation particularly for use for a reasonably large panel of countries, which allows us to assess the impact of patent enforcement across countries and the role of institutional quality in influencing the innovation process. Because the standards employed for granting patents (and assessing value of the patents), are not uniform across countries (Schankerman and Pakes, 1986; De Rassenfosse et al., 2016; De Saint-Georges and De la Potterie, 2013; Duggan et al., 2016), we employ patents recorded in the World Bank WDI to avoid concerns about lack of comparability in relation to patent data across the countries. Second, in many countries, no substantive examination is carried out before granting patents (De Rassenfosse et al., 2016). Therefore we include patents recorded in WDI as a proxy measure for ensuring the same standard for novelty of innovations that have been patented is applied.

Despite the importance attributed to innovation the development of methods for its measurement have lagged behind those for many other areas of economic and social life (Archibugi, 1988). Because the innovation process is intricate, iterative, incremental and often intangible arriving at an infallible measurement of innovation remains problematic (Hauser et al., 2018). Consequently, many different measures have been adopted, each with their own merits, idiosyncrasies and shortcomings. Many studies, for example, use the intensity and extensity of R&D expenditures as a proxy for innovation activity. While this data is widely produced and internationally standardised it does have significant drawbacks, not least given the uncertainty inherent to the scientific and technological process, since the input of R&D expenditure may not translate into innovative outputs. Similarly, these measures take no account of innovations which do not arise from the R&D expenditures. In contrast, innovation counts (derived from product announcements, specialised databases and bibliometric directories) and firm based surveys (data obtained directly from relevant companies) overcome these

Table 1
List of countries.

Argentina	France	Korea (South)	Slovenia
Australia	Germany	Malaysia	South Africa
Austria	Greece	Mexico	Spain
Belgium	Hong Kong	Netherlands	Sweden
Brazil	Hungary	New Zealand	Switzerland
Canada	Iceland	Norway	Thailand
Chile	India	Philippines	Turkey
China	Indonesia	Poland	USA
Colombia	Ireland	Portugal	Ukraine
Czech Republic	Israel	Romania	United Kingdom
Denmark	Italy	Russia	Venezuela
Estonia	Japan	Singapore	
Finland	Jordan	Slovakia	

Table 2
List of variables.

Variable	Variable definition
Patent enforcement*	JWB 2020 index of patent enforcement (0-10)
Patent enforcement squared	JWB 2020 index squared
GDP per capita†	GDP per capita, constant USD
Openness†	(Exports + Imports)/GDP (constant USD)
Log of population†	Population (logged)
Property rights‡	Property rights (0–100)
Health expenditures per capita†	Health expenditures per capita, USD
High technology exports†	High tech exports, current USD
Log of FDI †	FDI current USD (logged)
Logged R&D personnel†	Researchers engaged in R&D (per million people), logged

l shows natural logarithm of respective variable.
*: Patent enforcement index Papageorgiadis and Sofka (2020).
†: World Bank World Development Indicators 2019.
‡: Heritage Foundation Index of Economic Freedom (2020)

problems by looking at innovation outputs. While they tend to highlight innovations that are economically significant they also have shortcomings. Innovation counts tends to favour the implementation of radical and product innovations at the expense of more incremental and process oriented innovation while firm based surveys often suffer from arbitrary sampling and are difficult to compare internationally. Alternative techniques piloted by recent papers including textual analysis (Bellstam et al., 2021) seem to offer no obvious advantages over existing methods and are yet to be widely adopted (He and Tian, 2020).

This brings us to our preferred variable, the logarithm of the number of patents. Patents, too, have handicaps as a measure of innovation. On the one hand, patent counts may exaggerate levels of innovation because they measure inventions that may never be commercialised (Smith, 2005), thereby limiting their economic impact (Torrisi et al., 2016; Becheikh et al., 2006). Conversely, patent counts may understate levels of innovation since not all innovations are patented or patentable (Jensen et al., 2007; Hauser et al., 2018; Sweet and Eterovic, 2019). Given the costs of patenting many firms resort to other methods to prevent the appropriability of their innovations including commercial secrecy and technological complexity (Moser, 2005, 2012), something that is reflected in differing patent propensities between industries (Mansfield, 1986) and countries (Varsakelis, 2001). Equally, many innovations, especially in service industries (Hipp and Grupp, 2005) are covered by other types of protection such as copyright. Finally, patents tend to be associated with frontier technology and new-to-the market innovations. Patents nevertheless have important advantages as a measure of innovation and many authors fallback on this when using a single indicator of innovation (Hauser et al., 2018). Unlike most other measures of innovation patents are systematically registered, processed, classified and organized according to internationally agreed conventions. Concomitantly, compared to many other measures, patents counts are accessible, complete, internationally standardised and comparable, and stretch back a considerable period of time (Sweet and Maggio, 2015). The choice of patents as the dependent variable stems, partly, from the availability of a large time-series data set that includes both developing and developed countries. Moreover, although it is true that not all patents are commercially exploited, there is considerable evidence that companies do utilize patents to protect their innovations and, moreover, become the basis for commercial products (European Patent Office, 1994). Equally we are cognisant of the limitations of relying upon one measure of innovation, and this is reflected in the guarded nature of the some of the conclusions offered later in the paper. We use the logarithm of the number patents because patent data are right-skewed.

Our empirical models include the following independent variables as predictors of institutional quality. Property rights (*propright*) provide a measure of the strength of property rights institutions. We assess the role of property rights institutions on innovation by including the 'private property index' obtained from the Heritage Foundation (2020), widely used elsewhere to measure institutional quality related to the protection of private property (see for example (Acemoglu and Johnson, 2005; Kunčič, 2014; La Porta et al., 1999; Simón-Moya et al., 2014)). Ranging from 0 to 100, with a higher score indicating more certain legal protection of properties, this index denotes the degree to which private property is secured against expropriation by a national government or other organisations plus the extent to which a country's law protects private property rights. It thus assesses the ability of an individual or firm to accumulate private property in a country and the related probability of expropriation. It is therefore an important measure of institutional quality which has a significant impact on the likelihood of enforcement of laws, including patent protection laws and intellectual property rights laws more generally. An index of patent enforcement (*jwbi*) captures the *de facto* situation relating to IPR protection (varying between 0 and 10) (Papageorgiadis and Sofka, 2020). In choosing this index we depart from most previous studies (see for example Hudson and Minea (2013); Sweet and Maggio (2015)) that focus on the *de jure* strength of the patent systems, by using measures such as the Ginarte and Park (1997) index or use of count data variables such as laws and reforms (Chen and Puttitanun, 2005; Kanwar and Evenson, 2003; Allred and Park, 2007). Our choice is motivated by the fact that we are focusing on patent enforcement as a more accurate indication of institutional quality and also because enforcement is extremely important for explaining innovation outcomes. Papageorgiadis and Sofka (2020) construct the *JWBI* for the period 1998–2017, using panel data for 51 countries. Their methodology provides an overall composite patent enforcement index which we use in this paper. They include new data which takes into account the enforcement of patent laws rather than the mere existence of patent systems. Their methodological approach is based on transaction costs theory, whereby the *JWBI* decomposes overall strengths within patent enforcement into three sub-indices. These sub-indices are based on three transactions cost constructs capturing important aspects such as (i) those related to servicing costs (for example, patent administration quality), (ii) property rights monitoring costs (for example, judicial enforcement and corruption within the judiciary) and (iii) monitoring costs (for example, police enforcement and public commitment to patent protections). By using this approach, the *JWBI* incorporates suitable individual measures for each identified component and uses data for countries over time allowing intertemporal comparisons to be made. This enables the use of the overall *JWB* index for empirical analysis of impacts of cross-country patent enforcement within applied research (Further details are provided in a Technical Appendix to this paper). Following Furukawa (2010), Hudson and Minea (2013) and Sweet and Maggio (2015) we also include a squared term (*jwbisq*) for patent enforcement to encompass nonlinearities.

High technology exports are used to capture the country's pattern of specialisation and the institutional quality related to technological and production capabilities and the effectiveness of public policies focused on industrial upgrading, drawing on previous research (Anand et al., 2012; Lundvall, 1998; Zhu and Fu, 2013). The data for this variable are in current U.S. dollars and were obtained from the World Bank's WDI, which source them from the UN Comtrade database. High-technology exports include products with high R&D intensity, such as aerospace, computers, pharmaceuticals, scientific instruments, and electrical machinery.

The last dependent variable is the number of researchers engaged in R&D, expressed per million of population. The data were obtained from the World Bank's WDI, which source them from the UNESCO Institute for Statistics. According to this source, researchers are professionals who conduct research and improve or develop concepts, theories, models techniques instrumentation, software of operational methods. R&D includes basic research, applied research, and experimental development. As argued above, human resources engaged in R&D has been considered as a strong predictor of institutional quality in previous studies (Furman et al., 2002; Glaeser et al., 2004), and is often related to the existence of absorptive capacity (Huang et al., 2015) and the achievement of inventions and innovations (Herrera, 2020; Maggitti et al., 2013; Neuhäusler, 2012a; Salter et al., 2015).

Our empirical model also includes a number of control variables. Drawn from the World Bank's WDI, the gross domestic product (GDP) per capita is the gross domestic product divided by midyear population in constant 2010 U.S. dollars. GDP per capita is considered, by previous related studies, as a proxy of economic development (Chen and Puttitanun, 2005; Gamba, 2017; Kanwar and Evenson, 2003) and a measure of purchasing power (Allred and Park, 2007). Population was used as a proxy for market size as suggested by Sweet and Maggio (2015) and to control for scale effects (Gamba, 2017) related to the increase of innovation and inventors with population (Kremer, 1993; Simon, 1977). The data, obtained from the World Bank's WDI, reflects the countries' midyear estimate of total population, considering all residents regardless of legal status or citizenship, and was logarithmised. Openness is measured by the trade-to-GDP ratio, that is, the share of exports and imports in GDP. It was computed considering exports and imports of goods and services in current USD and GDP in current USD, using data from the World Bank's WDI. Previous studies have considered that openness benefits innovation (Grossman and Helpman, 1995), enabling the accumulation of physical and human capital (Wang and Wang, 2021) and the ease of exchange of ideas and technology transfer (Chen and Puttitanun, 2005; Porter and Stern, 2000; Varsakelis, 2001). Foreign direct investment (FDI) data were acquired from the World Bank's WDI, reflecting foreign direct investment net inflows, that is, investments to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor. Net inflows are computed as new investment inflows less disinvestment. Original data (in current U.S. dollars) was logarithmised. FDI is has been considered to be a proxy of availability of resources/-funding and a factor that enhances the possibilities for technology transfer (Grossman and Helpman, 1995; Hudson and Minea, 2013). Our final control variable is health care expenditures per capita. Healthcare expenditures have been widely used in studies concerned with innovation and, like them, we employ it owing to its strong association with other important covariates, including important ones such as human capital (Ghauri and Rao, 2009). Although the relationship is complex and is known to suffer from diminishing returns, cross-country studies posit a positive association between rising healthcare expenditures and, with some notable exceptions, and a range of health and wellbeing outcomes. For instance, van Stel et al. (2019) find that better health outcomes lead to improved earnings and greater output. Healthcare expenditures therefore represent a substantial investment in human capital (Barro, 1996), with enhanced wellbeing in turn leading to an enhanced and more productive workforce. Arguably, this is most important in developing economies where, relative to developed economies, the scarcity of capital and plentiful supply of labour makes the latter central to economic growth and productivity. Likewise, healthcare is a critical component of the 'soft infrastructure' (Khanna, 2012) which promotes (or inhibits) trade and investment. (Portugal-Perez and Wilson, 2012; Buckley, 2006). Unfortunately it is only in the last decade, thanks to the heroic efforts of the UN and the OECD (see Woodward (2022)), that standardised and internationally comparable wellbeing data has become available. Nevertheless, many important variables that we would like to include in our analysis are not available in a comparable format for our sample of countries. For this reason, we have resorted to data on total expenditure on healthcare goods and services per capita (in current US dollars) provided by the World Bank's WDI which incorporates a very large number of countries for the period under investigation.

Table 3 shows summary statistics for our variables listed in Table 2. There are a large number of missing values for high technology exports (*lhtxcur*) but given the theoretical importance of this variable and the emphasis placed on its inclusion in the empirical literature, it is retained in our analysis.

Table 3
Summary statistics.

	Obervations	Mean	SD	Min	Max
Log of patents	862	8.438	1.819	3.219	14.139
Patent enforcement	874	5.948	2.334	0.100	9.700
Patent enforcement squared	874	40.821	27.128	0.010	94.090
GDP per capita	897	9.778	1.082	6.631	11.425
Openness	878	0.842	0.557	0.153	3.957
Log of population	900	16.959	1.602	12.521	21.050
Property rights	900	67.259	22.630	0.000	97.100
Health expenditures per capita	806	6.957	1.454	2.785	9.212
High technology exports	461	23.053	1.976	17.473	27.209
Logged FDI	860	22.920	1.650	14.509	27.322
Logged R&D personnel	684	7.524	1.125	3.907	9.029
N	900				

4.2. Empirical results and discussion

In this section, we provide a discussion of results obtained from empirical analysis using OLS, panel regression and UQR methods. Table 4 shows the results of OLS and panel estimations (fixed effects and random effects). Confirming the findings of previous research (Hudson and Minea, 2013; Qiu and Yu, 2010; Sweet and Maggio, 2015), our pooled OLS model finds a significant and positive sign for the square of the patent enforcement index, per capita GDP, population or market size and researchers engaged in R&D. In contrast to some findings (see for example Schneider (2005)) the coefficients for FDI and health expenditures are significant but, counter-intuitively, point towards a negative relationship. Unexpectedly, the indices for patent enforcement (*jwbi*) and property rights (*propright*) as well as high technology exports (*lhexppc*) are all insignificant. Results in Table 5 clearly show that the fixed effects (FE) model is preferred at the 5% and 10% significance level based on the Hausman test and the Sargan-Hansen statistic. The random effects (RE) model is marginally not rejected at 1% significance level. The index of patent enforcement and the squared term of the index patent enforcement are both insignificant for the FE model, while only the former is significant for the RE model. For the FE model, per capita GDP, openness, population, health expenditures, high technology export and researchers engaged in R&D are significant, while the rest of the variables are insignificant. Given that the diagnostics in Table 5 suggest that a fixed effects model is preferred, the OLS and FE models provide scant evidence that patent enforcement has an impact on innovation outcomes, giving succour to studies which conclude:

> the impact of strengthened patent protection may simply be far less on innovative activities than much of the economic and policy literature assumes. (Lerner, 2009, p. 348, p. 348)

However, our OLS results contradict the overwhelming majority of empirical (Kanwar and Evenson, 2003; Chen and Puttitanun, 2005; Moser, 2005; Sweet and Maggio, 2015; Hudson and Minea, 2013) and theoretical (Grossman and Lai, 2004; Scotchmer and Green, 1990) research which demonstrates a strong, if varying and complex, relationship between IPR, innovation and patenting.

When compared with OLS and panel regressions, the UQR results

Table 4
Regression results - OLS, Fixed Effects and Random Effects.

	OLS	FE	RE
Dependent	Log of patents	Log of patents	Log of patents
Patent enforcement	−0.229	−0.174	−0.189*
	[0.1506]	[0.1302]	[0.0915]
Patent enforcement squared	0.0368***	0.00975	0.0126
	[0.0015]	[0.2891]	[0.1596]
GDP per capita	0.709***	1.007***	0.707***
	[0.0088]	[0.0004]	[0.0010]
Openness	0.0479	−0.878***	−0.782***
	[0.7710]	[0.0000]	[0.0000]
Log of population	1.479***	−1.192**	0.809***
	[0.0000]	[0.0420]	[0.0000]
Property rights	0.008	0.00348	0.00498*
	[0.1438]	[0.2360]	[0.0872]
Health expenditures per capita	−0.510**	−0.355***	−0.456***
	[0.0105]	[0.0002]	[0.0000]
High technology exports	0.0601	0.191***	0.245***
	[0.3509]	[0.0007]	[0.0000]
Logged FDI	−0.196***	0.0096	0.0144
	[0.0000]	[0.4718]	[0.2819]
Logged R&D personnel	0.399***	0.402***	0.310***
	[0.0000]	[0.0000]	[0.0001]
Constant	−20.62***	14.57	−16.39***
	[0.0000]	[0.1198]	[0.0000]
Time fixed effects	YES	YES	YES
N	325	325	325
R^2	0.8133	0.2401	–

p-values in brackets.$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5
Panel diagnostic tests.

Hausman Test
Ho: difference in coefficients not systematic
chi2(10) = 21.83
Prob > chi2 = 0.0160
Test of overidentifying restrictions: fixed vs random effects
Sargan-Hansen statistic: 22.255
Chi-sq *p*-value = 0.0139

presented in Table 6 paint a strikingly different picture for the determinants of innovation outcomes. Specifically, they detect relationships that are overlooked or misrepresented by OLS or panel estimations, which disregard distributional aspects. Whereas the OLS and FE results find little evidence of a statistically significant relationship between patent enforcement and innovation outcomes, UQR conveys a more gradated impression finding that patent enforcement is negative and significant towards the left of the distribution between $\tau = 0.10$ and $\tau = 0.20$, and positive and significant for patent enforcement at $\tau = 0.60$. For the squared term of patent enforcement, we find that patent enforcement is positive and significant between $\tau = 0.10$ and $\tau = 0.20$, and positive and significant at $\tau = 0.60$. From this we can infer that at lower quantiles tougher patent enforcement inhibits innovation outcomes (as measured by patents). Given the magnitude of the coefficients, these findings strongly support the argument that whilst sustaining innovation requires a minimal or threshold level of IPR protection, excessive enforcement can reduce innovation, especially in developing economies where the threat of legal recourse may deter low end imitators (Gangopadhyay and Mondal, 2012).

The coefficients for property rights (Fig. 5) show a rise until $\tau = 0.15$, then a fall until a minima is reached at $\tau = 0.55$, with a monotonic increase until a maxima is reached at $\tau = 0.80$. These results show that towards the right of the distribution property rights have a significant positive effect on innovation outcomes especially from $\tau = 0.70$ to $\tau = 0.90$. This indicates that for countries with capabilities for producing large volumes of patents stronger property rights enable further innovation. The estimated UQR coefficients for the GDP variable are equally informative. At the left hand side of the distribution, from $\tau = 0.10$ to $\tau = 0.25$, there is a strong and significant positive relationship between GDP and innovation. Conversely, at the right hand side of the distribution, we find a significant and strongly negative relationship for innovation outcomes (as measured by patents) from $\tau = 0.75$ to $\tau = 0.90$. Previous research shows that the impact of IPR on innovation is closely linked to levels of development (Chen and Puttitanun, 2005; Allred and Park, 2007; Hudson and Minea, 2013). High GDP levels may well be indicating that sophisticated and strict IPR regimes in developed economies are muzzling innovative activity. These findings are relevant to the ongoing debate about optimal levels of patent protection. In addition to suppressing innovation in relatively underdeveloped economies, there is abundant evidence that overzealous IPR regimes can hinder further technological catch-up in economies that are already innovative (Qian, 2007), with extra protection serving to boost the rents to patent holders rather than rewarding the resourcefulness of innovators (Qiu and Yu, 2010). These authors posit the existence of an inverted U-curve between the stringency of IPR and innovation (Furukawa (2007); Furukawa (2010); Horii and Iwaisako (2007)). In other words, there is a threshold beyond which the added incentives provided to innovators by tougher IPR are outstripped by the drag on innovation prompted by the monopoly powers bestowed upon patent holders (Bessen, 2009; Woo et al., 2015).

We next present the results obtained from unconditional quantile partial effects graphs (UQPE) which foreground further interesting insights into underlying relationships. Fig. 2 shows the effect of patent enforcement on innovation outcomes, as measured by the log of patents (*lpatents*). As outlined above, the coefficient falls initially, but then rises monotonically until about $\tau = 0.45$, levelling off (showing positive values) and then peaking at $\tau = 0.60$ after which there is a decline followed by a sharp upswing at $\tau = 0.90$. These results, especially the strong and significant result at $\tau = 0.60$, indicate support for the U-shaped innovation-IPR enforcement argument illustrated for example in Furukawa (2010). These results infer that innovation is best sustained by moderate IPR enforcement regimes, especially when innovation related capabilities are weak. Equally, the estimated coefficient at $\tau = 0.90$ suggests that stronger IPR enforcement regimes support innovation but only in the most innovative economies, but this result is statistically insignificant. Furthermore, for the left of the distribution where results are significant ($\tau = 0.10$ to $\tau = 0.20$), the UQR coefficients in Fig. 2 suggest a much stronger positive relationship between IPR enforcement and innovation than that implied by OLS. These results indicate that an exclusive reliance on OLS or panel results may lead to biased or incorrect inferences. Likewise, UQR enables us to more accurately ascertain correlations at various points of the distribution, providing greater context and clarity.

Emboldened by free market policy guidance, many countries have liberalised their economies to international trade, seeking higher exports as an engine of growth and development. Exposure to international competition forces domestic firms to innovate, especially if they want to succeed in markets overseas. Patents are often a by-product of the intense innovation activity required to support high technology exports. Empirical investigations of this strategy suggest that the quantity of exports is less important than their quality (Hausmann et al., 2007). Reflecting a cumulative learning process, high levels of complex exports are indicative of an economic environment whose institutional underpinnings foster innovation (Zhu and Fu, 2013). Our UQR results suggest considerable variation across the distribution. Looking at Fig. 3, the coefficient of high technology exports initially rise until $\tau = 0.15$, thereafter falling until $\tau = 0.4$ is reached. The values then rise until $\tau = 0.6$ followed by a fall and another peak at $\tau = 0.75$, followed by another decline into negative territory after which a maximum value is attained at $\tau = 0.90$. We find a positive and significant coefficient for high technology exports at $\tau = \{0.6, 0.75, 0.9\}$ implying a strong relationship between high technology exports and levels of innovation. Equally, however, the UQR results also show a positive coefficient until $\tau = \{0.25\}$, which is significant at $\tau = \{0.15\}$ and, likewise the coefficients dip into negative territory on the right side of the distribution at $\tau = \{0.80, 0.85\}$. Negative coefficients also prevail in the middle of the distribution from $\tau = \{0.25\}$ to $\tau = \{0.50\}$, being significant at $\tau = \{0.40, 0.45\}$. The relationship between high-tech exports and innovation outcomes is thus less clear cut than suggested by the OLS (insignificant coefficient) and FE (positive and significant coefficient) models in Table 4.

Endogenous growth theory emphasises the importance of human capital in driving innovative activity. High quality human capital facilitates the diffusion of new technologies (Benhabib and Spiegel, 2005) and the absorption of innovations made elsewhere (Nelson and Phelps, 1966). For these reasons, it is unsurprising that our OLS and FE models find a positive and significant relationship between human resources in R&D and innovation outcomes. UQR, however, reveals some additional dimensions to this relationship. The UQR coefficient for researchers engaged in R&D is positive from $\tau = 0.35$ and is also significant between $\tau = 0.40 - 0.50$ and $\tau = 0.80 - 0.90$. Noticeably the coefficients on the far right-hand side of the distribution using UQR (see Fig. 4) are four to five times greater than those indicated by OLS, suggesting human resources devoted to R&D yield a significant increase in innovation outcomes within the most innovative economies. This clearly points towards better training, skills and education within human capital employed within the most innovative economies which in turns enhances their innovation capabilities. Conversely, the coefficient for researchers engaged in R&D is negative and significant between $\tau = 0.10 - 0.25$ suggesting that for the less innovative economies it is not enough to increase the number of researchers to raise the innovation outcomes.

Table 6
UQR results.

Quantile (τ)	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45
Dependent variable = *lpatent*								
Patent enforcement	−1.973***	−2.442***	−1.897***	−0.797	−0.238	0.166	0.363	0.382
	(-0.378)	(-0.319)	(-0.587)	(-0.549)	(-0.396)	(-0.318)	(-0.286)	-(0.253)
Patent enforcement squared	0.156***	0.209***	0.194***	0.101**	0.04	0.007	−0.018	−0.017
	(-0.029)	(-0.025)	(-0.042)	(-0.048)	(-0.034)	(-0.025)	(-0.021)	(-0.019)
GDP per capita	2.552**	2.544***	2.240***	1.263**	0.679	0.134	0.574	0.706
	(-1.132)	(-0.664)	(-0.609)	(-0.637)	(-0.605)	(-0.507)	(-0.551)	(-0.469)
Openness	−0.125	−0.755**	−0.387	0.164	0.517	0.573**	0.663**	0.647**
	(-0.557	(-0.369	(-0.447	(-0.387	(-0.347	(-0.28	(-0.317	(-0.315
Log of population	1.094*	0.715***	1.190***	1.255***	1.246***	1.223***	1.386***	1.456***
	(-0.591)	(-0.272)	(-0.257)	(-0.201)	(-0.183)	(-0.206)	(-0.225)	(-0.216)
Property rights	0.004	0.021	0.01	0.003	0.002	−0.003	−0.002	−0.009
	(-0.021)	(-0.015)	(-0.013)	(-0.01)	(-0.009)	(-0.009)	(-0.01)	(-0.012)
Health expenditures per capita	−1.047*	−1.631***	−1.356***	−0.651	−0.273	−0.254	−0.587	−0.754**
	(-0.588)	(-0.452)	(-0.495)	(-0.462)	(-0.411)	(-0.362)	(-0.369)	(-0.312)
High technology exports	0.168	0.479***	0.068	−0.068	−0.078	−0.12	−0.252**	−0.236*
	(-0.228)	(-0.167)	(-0.191)	(-0.123)	(-0.113)	(-0.118)	(-0.127)	(-0.134)
Logged FDI	0.073	−0.156	−0.159*	−0.117	−0.054	0.04	0.015	−0.126
	(-0.112)	(-0.105)	(-0.085)	(-0.089)	(-0.082)	(-0.089)	(-0.09)	(-0.09)
Logged R&D personnel	−0.438*	−0.807***	−0.672***	−0.418***	−0.284	0.274	0.439**	0.618***
	(-0.249)	(-0.208)	(-0.204)	(-0.162)	(-0.26)	(-0.255)	(-0.182)	(-0.165)
Constant	−26.769**	−14.604***	−15.120***	−13.838***	−13.775***	−14.187***	−16.723***	−16.024***
	(-12.704)	(-5.025)	(-3.439)	(-2.931)	(-3.24)	(-3.372)	(-3.585)	(-3.537
Time fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	325	325	325	325	325	325	325	325
R-squared	0.48	0.536	0.553	0.51	0.505	0.482	0.502	0.523

Standard errors in brackets.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

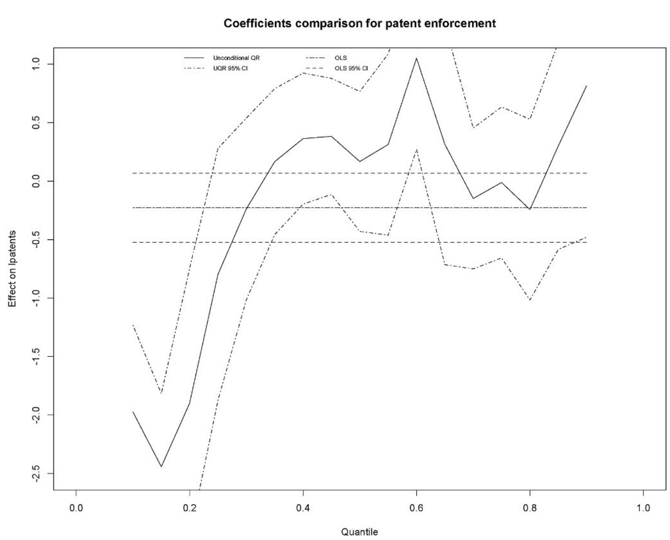

Fig. 2. Effect of jwbi on lpatents.

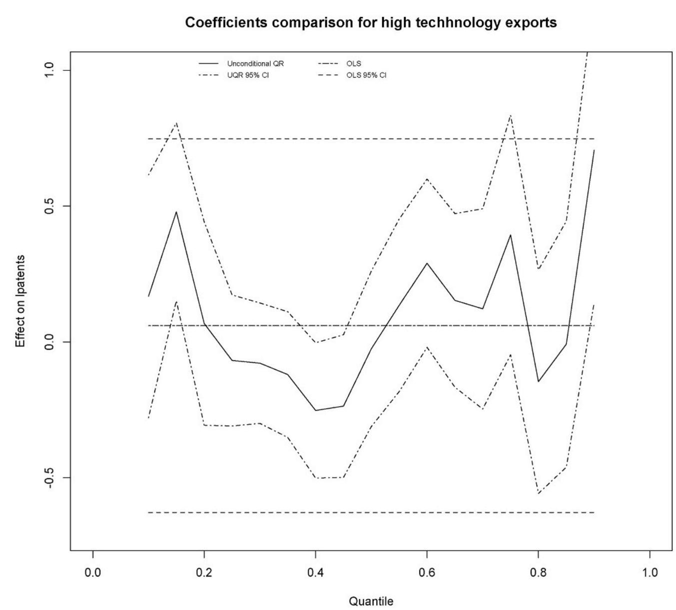

Fig. 3. Effect of htx on lpatents.

This counter-intuitive result may be accounted for several factors affecting the productivity of researchers. Again, this might be indicative of the importance of the quality of the human resources, namely in terms of education, competence and motivation (Ballesteros-Rodríguez et al., 2020; De Rassenfosse and de la Potterie, 2009). Perhaps the most compelling explanation, however, may lie in the underlying structures of the different economies, their differing propensities for undertaking R&D and the purposes to which it is put. Harking back to the preceding discussion of patents as a proxy for innovation, research has demonstrated significant differences in the intensity and types of R&D between industrial sectors (see for example (Archibugi, 1992; Dosi et al., 2006; Basberg, 1987; X.Cirera and Maloney, 2017) and between the public and the private sectors (Barirani et al., 2015).[1] For example, relatively lower level of patenting may be the outcome of R&D being dominated by the public sector which is perhaps less likely to seek patents to exploit inventions for commercial exploitation. R&D activities may also be skewed towards industries where innovations are not 'patentable' (Sweet and Eterovic, 2019), where different methods of intellectual

[1] We would like to thank one of our anonymous reviewers for drawing our attention to this point.

0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90
0.167	0.312	1.050***	0.314	−0.149	−0.012	−0.244	0.299	0.814
(-0.305)	(-0.395)	(-0.398)	(-0.525)	(-0.307)	(-0.329)	(-0.394)	(-0.451)	(-0.66)
0.013	0.007	−0.051*	−0.014	0.006	0.002	0.034	−0.008	−0.066
(-0.023)	(-0.029)	(-0.028)	(-0.029)	(-0.021)	(-0.026)	(-0.032)	(-0.034)	(-0.053)
0.562	0.525	0.918*	0.63	0.314	−1.742*	−1.703**	−2.135***	−2.544**
(-0.519	(-0.586	(-0.548	(-0.574	(-0.815)	(-0.996)	(-0.72)	(-0.716)	(-1.195)
0.397	0.263	0.065	0.631	0.699	−0.86	−0.706	−0.242	−0.486
(-0.304	(-0.377	(-0.459	(-0.478	(-0.655	(-0.773	(-0.431	(-0.38	(-0.589
1.225***	1.048***	0.975***	1.407***	1.594***	1.021***	1.958***	1.869***	1.958***
(-0.223)	(-0.246)	(-0.286)	(-0.318)	(-0.317)	(-0.351)	(-0.362)	(-0.307)	(-0.538)
−0.016	−0.022*	−0.006	0.019	0.037***	0.054***	0.079***	0.059***	0.066***
(-0.012)	(-0.013)	(-0.012)	(-0.017)	(-0.012)	(-0.017)	(-0.015)	(-0.017)	(-0.024)
−0.897**	−0.701*	−1.076**	−0.398	0.225	0.701	0.073	0.544	0.856
(-0.355)	(-0.383)	(-0.442)	(-0.505)	(-0.497)	(-0.437)	(-0.56)	(-0.542)	(-1.018)
−0.025	0.135	0.290*	0.153	0.122	0.394*	−0.146	−0.008	0.706**
(-0.146)	(-0.162)	(-0.158)	(-0.163)	(-0.188)	(-0.225)	(-0.21)	(-0.231)	(-0.286)
−0.175**	−0.194**	−0.211**	−0.250***	−0.217*	−0.037	−0.045	−0.289	−0.880**
(-0.075)	(-0.082)	(-0.094)	(-0.091)	(-0.127)	(-0.114)	(-0.118)	(-0.214)	(-0.344)
0.543***	0.26	0.015	0.193	0.315	0.703	1.850***	1.716***	2.130***
(-0.183)	(-0.224)	(-0.206)	(-0.189)	(-0.243)	(-0.47)	(-0.406)	(-0.35)	(-0.734)
−11.744***	−10.871***	−14.855***	−20.681***	−25.453***	−12.478**	−21.386***	−15.730***	−21.651**
(-3.905)	(-4.209)	(-5.366)	(-6.11)	(-5.434)	(-5.252)	(-5.438)	(-5.092	(-10.851)
YES	YES	YES	YES	YES	YES	YES	YES	YES
325	325	325	325	325	325	325	325	325
0.52	0.469	0.522	0.516	0.535	0.584	0.549	0.422	0.388

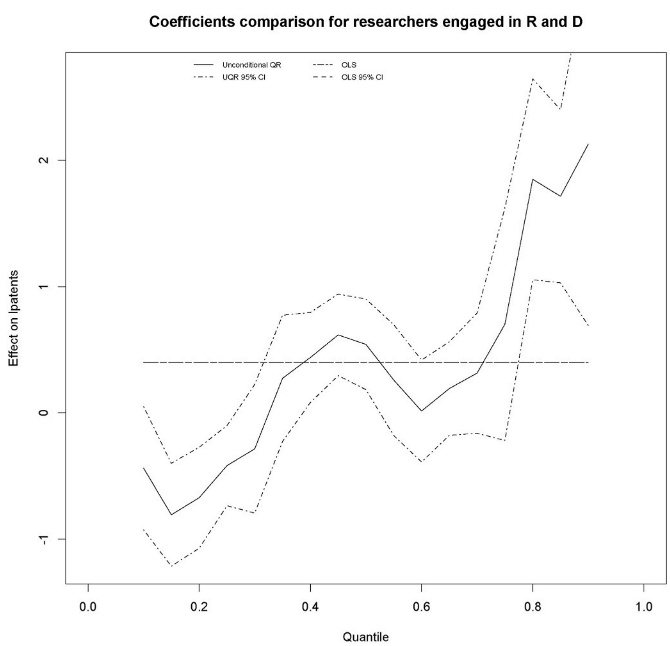

Fig. 4. Effect of resrd on lpatents.

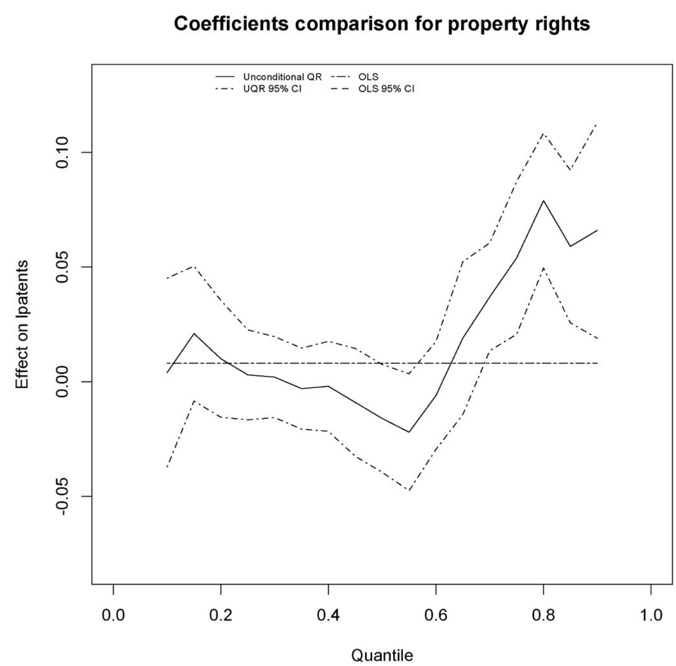

Fig. 5. Effect of proprights on lpatents.

property protection predominate. Testing these propositions, however, remains difficult not least because of limitations in available R&D data for developing countries (Gaillard, 2010). Irrespective, our results suggest that unless less innovative economies possess the necessary expertise, motivation, infrastructure, and industrial structure throwing extra human resources at R&D is unlikely to yield improvements to innovation outcomes.

Fig. 5 shows the effect of property rights on innovation outcomes. The coefficient of property rights first rises, peaking at $\tau = 0.15$ and then falls until $\tau = 0.55$, after which it rises monotonically until $\tau = 0.75$. Finally, it falls until $\tau = 0.85$, rising up again to reach a local maxima at $\tau = 0.90$. The clear and significant positive effect towards the right of the distribution between $\tau = 0.70$ and $\tau = 0.90$, indicates the importance of property rights protection on innovation outcomes. Given strong property rights, innovations and new knowledge are protected and appropriability of innovative activity and benefits thereof become easier to realise. This, in turn, faciliates further innovation.

5. Conclusion

There is almost universal agreement that innovation is central to the process of economic development. Innovative activity is recognized as one of the key factors accounting for variations in growth, productivity, and competitiveness between firms and countries. This has led to a vast and perpetually expanding research agenda devoted to identifying the conditions conducive to maximising an economy's innovative capacity. This paper empirically assesses the determinants of innovation, with particular focus on institutional characteristics and evidence for patent enforcement, to make a threefold contribution to the literature. First, we believe this is the first paper to employ UQR techniques to model determinants of innovation outcomes for a panel of countries. By employing UQR techniques, in addition to conventionally employed methods such as OLS and panel regressions, our paper highlights the complexities inherent in the factors underlying successful innovation and the importance of considering the entirety of the distribution to assess underlying relationships accurately. For example, our results suggest that there are significant differences in the nature and magnitude of relationship between our dependent variables within the most and least innovative economies, which conventional methods omit or misinterpret. As expected, the application of standard regression techniques finds a positive relationship between higher proportions of researchers engaged in R&D. The implementation of UQR, however, allows us to tease out more intricate relationships, not least that the effects of R&D are much more pronounced in the most innovative economies and may have negative outcomes in less innovative economies. These findings have important implications for policymakers. For example, our UQR results suggest that excessively strict patent enforcement is harmful for the least innovative economies. Likewise, while increasing the level of human resources devoted to R&D is highly beneficial in the most innovative economies, it is much less so within less innovative economies which typically tend to include developing countries. In contrast to the one size fits all approaches propagated by many international bodies, the constellation of policies necessary to promote innovation must be tailored to specific national contexts in a way that acknowledges their existing levels of innovative capacity.

UQR's utility is further demonstrated by our second contribution concerning the relationship between IPR enforcement and innovation outcomes. Much previous research examining the relationship between IPR and innovation rests on the flawed assumption that the mere existence of laws and regulations provides an adequate measure of IPR protection. In fact, as a growing number of commentators maintain (Maskus, 2014; Brander et al., 2017), it is the effective *enforcement* of IPR legislation that incentivises innovation activity. To this end, our paper utilises a recently expanded measure of patent enforcement in order to examine how the enforcement of IPR law affects innovation outcomes. According to our OLS model, tougher patent enforcement has no significant impact on innovation outcomes. In contrast, UQR results find clear support for a possible nonlinear relationship between IPR and innovation outcomes. Our statistically significant UQR results, especially the strongly negative relationship revealed towards left of the distribution and the positive relationship at the right of the distribution, indicate the there may also be an optimal level of IPR enforcement. Finally, our use of a panel data set spanning fifty countries over two decades (1998–2017) addresses methodological issues related to data limitations within prior research and make our empirical analysis more robust. We add to prior literature by employing data covering a significant time period as well as a broader sample of countries covering both developed and developing economies. These insights are particularly important given the way that TRIPS and other international treaties are forcing international harmonisation of *de jure* legal positions relating to IPR. Dwindling differences in the statute book will heighten the importance of enforcement as a factor in the promotion of innovation outcomes.

Our paper highlights practical ways to enhance understanding of the determinants of innovation outcomes and the role of institutional quality. We argue that UQR methods provide an additional set of tools for analysis within this field. Future research can make use of this, and other appropriate and evolving methods, to provide additional insights into the processes driving innovation outcomes, especially within a cross-country and inter-temporal setting. By employing suitable indices, such as the patent enforcement index, we can include suitable proxies within our analysis for hitherto omitted but important variables. UQR analysis is valuable for identifying interesting insights based on analysis across the distribution of key variables.

Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.technovation.2022.102562.

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