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Abstract

This paper explores the nexus between innovation and bureaucratic performance where we focus on the effect of actual bureaucratic performance, rather than bureaucratic capacity. A conditional difference in differences estimation using an unbalanced panel of nations spanning the period 2004-2018, provides strong evidence that better bureaucratic performance underlies better innovation outcomes, ceteris paribus. At the median stock of knowledge capital, a one-unit improvement in bureaucratic performance raises the patent applications of a sample country by about 1813, which constitutes a 5.0% increase over the sample mean patent applications. Second, this effect is heterogenous, with this response becoming more pronounced at higher percentiles of the knowledge capital stock owned by a country. Thus, at the 95th percentile, a one-unit increase in bureaucratic performance raises patent applications by 2329 or about 6.5% of the respective sample mean. This response is about 28% larger than that at the median stock of knowledge capital. Third, the strong significance of bureaucratic performance for innovation is found to be fairly broad-based across technology groups such as Electrical/Electronics technology, Professional and Scientific Equipment, Pharmaceuticals, Chemicals, and Machinery (Non-electrical), and therefore is not driven by just one or two of these groups. The results are robust to several robustness checks.

Keywords: Innovation, Bureaucratic performance, heterogenous response

JEL codes: O34, O38, O43

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1. Introduction

Neo-classicists would argue that the interaction of the demand for and supply of knowledge emanating from self-interested agents leads to the optimal innovation outcome, as if led by an invisible hand. Numerous economists have explained, however, that this paradigm does not work well when markets are unfree and/or incomplete, as is true of the market for knowledge, and in those situations "the invisible hand often seemed invisible because it was not there" (Stiglitz 2008). Since laissez-faire is likely to lead to sub-optimal innovation outcomes, this implies a role for public policy, wherein government bureaucracy is meant to replace and/or guide the invisible hand in framing and executing the public innovation policies. Consequently, if the 'visible hand' of bureaucracy is deficient in any manner, that will evidently have implications for the magnitude and quality of innovation conducted in that country.

Analyses of innovation and technological change, however, mostly take for granted the existence of a well-oiled bureaucratic machinery. Thus, while there is debate about what policies would be conducive for innovation – whether public sector R&D investment would be the appropriate instrument, whether private sector R&D investment ought to be encouraged, whether venture capital funding ought to be made available by the public sector, how strong should patent and copyright protection be, etc. – the *efficacy* of the bureaucracy that will be called upon to formulate and implement the policies is not given the attention it ought to be. Needless to say, this could be a big error, not only in the context of resourcestrapped less developed countries but developed nations as well, as anecdotal evidence reminds us every so often.[1]

Although it tends to be the case all over the world that government bureaucracy is bound by excessive and rigid rules, that it is answerable to multiple authorities with often conflicting goals, that it suffers from multiple hierarchies and that it is saddled with disparate tasks of varying complexity (Dixit 2012), the extent and form of these constraints vary significantly across countries and over time. It is these differences that underscore the fact that government bureaucracy in some countries is much more dynamic, responsive and efficient than in others, with concomitant positive implications for innovation outcomes in those countries.[2]

The extant literature in this area is rather thin. What one does find are studies pertaining to the relationship between bureaucracy and economic growth. Though these are relevant to our context, it is necessary to emphasise that bureaucracy can influence economic growth by impinging on a number of factors, of which innovation may or may not be one. Therefore, whether bureaucratic performance has any bearing on innovative activity per se is something that needs to be established, and ought not to be taken for granted on the basis of studies pertaining to its effect on economic growth.

With this caveat in mind, we note that Johnson (1982) for Japan, Amsden (1989) for South Korea, Wade (1990) for Taiwan, and Haggard (1990) for some East Asian and Latin American newly industrialising countries, were some of the early case studies that revealed the role of government agencies in encouraging economic growth in those countries. However, amongst the first to establish this relationship formally were Evans and Rauch (1999), who found a significant positive relationship between bureaucratic structure (specifically, meritocratic recruitment and stable careers) and economic growth in less developed countries. This result was confirmed by Henderson et al. (2007) in the context of poverty reduction, and Nee and Opper (2009) for financial market development, while Kurtz and Shrank (2007) report an insignificant influence of bureaucracy on economic growth. A strand of this literature focuses on the link between corruption and economic growth (see, for instance, the interesting paper by Aidt (2009), as well as the citations therein; also Gruendler and Potrafke 2019). However, corruption is only one dimension of bureaucratic (in)efficiency, and would need to be buttressed by other factors to capture the effect of bureaucratic performance 'as a whole' on growth. Dougherty and Corse (1995) is amongst the few studies that explores the bureaucracy-innovation nexus specifically, and using survey evidence, shows that certain bureaucratic attitudes or values could be inimical to (firm-level product) innovation. Also of interest is Barbosa and Faria (2011) who show that stronger labour and product market regulation significantly discourages innovation intensity (or the proportion of firms which report having introduced an innovation), while credit market regulation has the converse effect.[3]

The received literature, however, has a number of shortcomings from our viewpoint. Virtually none of these studies establish a link between bureaucratic performance and innovative activity per se; rather they mostly study the relationship between (aspects of) bureaucracy and some dimension of economic growth (such as per capita income growth, or poverty alleviation, or financial development). Further, several of the earlier studies are case studies of individual countries, and do not establish a *formal* link between bureaucratic efficiency and the growth aspect of interest in those case studies. Furthermore, this literature uses cross section data, and does not adequately control for cross-section differences of unobserved characteristics. Our paper attempts to correct for these shortcomings, and contributes to the existing literature in several ways. First, it is amongst the very few to explore the significant issue of how variation in bureaucratic performance across nations influences innovation specifically. Second, in investigating this relationship, we focus on the effect of actual bureaucratic performance or what the bureaucracy *actually* delivers, rather than bureaucratic capacity or what the bureaucracy *could* deliver. Implicit in this emphasis are concerns pertaining to inefficiencies in bureaucratic decision-making which raise the time and cost of various projects, including research projects. For instance, it is well-known that the public sector supports inventive effort insofar as it supports R&D in various public sector laboratories and universities, and provides competitive funding to private laboratories and universities. However, it will not help if it diminishes that effort via poor performance, which raises the time and cost for various players in the economy, and thereby diverts scarce resources, hurts incentives and reduces motivation (see also, Mohr 1969). This likely has consequences for the magnitude and quality of innovation in an economy. Third, our estimation framework allows for a possible heterogeneity in the relationship between bureaucratic performance and innovation, varying as it does by the stock of knowledge capital a country owns. And finally, we explore whether the relationship in question holds across several technology categories or is driven by just one or two.

Estimating a conditional difference in differences specification using an unbalanced panel of countries spanning the period 2004-2018, our results provide clear and strong support for the contention that better bureaucratic performance underlies better innovation outcomes, ceteris paribus. The empirical estimates suggest, that at the median stock of knowledge capital, a one-unit improvement in bureaucratic performance raises patent applications of a sample country by about 1813. This change is substantial, translating into a 5.0% increase over the sample mean patent applications. Second, this effect is heterogenous, such that this response becomes more pronounced at higher percentiles of the knowledge capital stock. Thus, at the 95th percentile, the effect of a one-unit increase in bureaucratic efficiency is to raise total patent applications by 2329 or about 6.5% of the sample mean patent applications. This is about 28% larger than that at the median knowledge-capital stock, underlining the heterogenous response. Third, the strong significance of bureaucratic performance for innovation does not seem to be driven by just one or two of the technology groups, but is found to be fairly broad-based across the various technology groups such as Electrical/Electronics technology, Professional and Scientific Equipment, Pharmaceuticals, Chemicals, and Machinery (Non-electrical). The results are found to withstand several robustness checks.

Section 2 explains the modelling strategy employed in this paper, and the estimation specification. Section 3 provides a discussion of the variables employed, and the data used for estimation. Section 4 presents the empirical results and various robustness checks. Section 5 briefly concludes the paper.

2. The Model Specification

We study the relationship between the innovation output in a country and its bureaucratic performance via a conditional difference in differences approach. Patents, for long, have been considered a valid, even if imperfect, measure of innovation output (Griliches 1990; Madsen 2007), so we represent innovation by the aggregate patent applications of a country per capita (World Intellectual Property Organization 2022). Denoting innovation as PAT_PC_{it} and bureaucratic performance as $BUREAU_{it}$, where i indicates the country and t the year, consider the effect of variable $BUREAU$ as the average effect in the panel regression

$$PAT\_PC_{it} = M_{it}(BUREAU) = m(BUREAU_{it}) + \alpha_i + \delta_t + \varepsilon_{it} \qquad (1)$$

where M is an unknown function that can vary across countries and time, and m is a specific conjecture about that function. The latter states that there is a systematic impact of bureaucratic performance $BUREAU_{it}$ that can be additively separated from fixed deviations by country and time (the country fixed effects α_i and year fixed effects δ_t), and an idiosyncratic error ε_{it}. Normally, m is specified as linear, and uniform over time and space, i.e. $m(BUREAU_{it}) = \beta * BUREAU_{it}$, plus some linear terms in the control variables Z_{it} (which we ignore for the moment).

It would be reasonable to argue, however, that higher bureaucratic performance does not have an identical effect on all countries in all years, but is likely heterogeneous, implying that β per se is not very informative. Furthermore, it is plausible that deviations from the average effect β are likely to be systematic and not independent of $BUREAU_{it}$. Therefore, using a specification such as $PAT\_PC_{it} = \beta\ BUREAU_{it} + (\beta_{it} - \beta)\ BUREAU_{it} + \alpha_i + \delta_t + \varepsilon_{it}$, which is equivalent to (1) but highlights the functional misspecification of a typical linear specification, it is evident that even when the treatment variable is exogenous, it is not necessarily so if one omits the second term which would then be absorbed into the mean independent deviation term ε_{it}. This would render the indicator endogenous, if the deviation from the average effect or $(\beta_{it} - \beta)\ BUREAU_{it}$ is not independent of $BUREAU_{it}$. One way of addressing this problem is to model β_{it} suitably, for instance via varying coefficients (Sperlich and Theler 2015) in a conditional difference-in-differences specification context (Frölich and Sperlich 2019).

We model β_{it} as a function of the extent to which countries stand to benefit from improved bureaucratic performance, where this country-specific benefit may vary over time, so that we can express it as X_{it} for country i in year t. Since X_{it} is possibly correlated with other factors relevant for the dependent variable PAT_PC_{it}, we control for those other factors as well. For this purpose, our fixed effects specification (1) is sufficient to account for country-specific time varying confounders Z_{it}, yielding the specification:

$$PAT\_PC_{it} = \beta(X_{it})\, BUREAU_{it} + \gamma Z_{it} + \alpha_i + \delta_t + \varepsilon_{it} \quad (2)$$

where $\beta(X_{it})$ indicates a function of X_{it}. As a first approximation, we hypothesize $\beta(.)$ as a linear function such as $\beta * (a + bX_{it})$. We represent factor X_{it} by the stock of knowledge capital of a given country in a given year ($KNOWCAP_{it}$). Evidently, the larger the research and development investment undertaken by a country, and the larger therefore its knowledge capital stock, the more it would stand to benefit from higher bureaucratic performance, for the level of bureaucratic performance would determine the productivity of the knowledge capital in generating innovation. Thus, we may re-write specification (2) as:

$$PAT\_PC_{it} = \beta_1 BUREAU_{it} + \beta_2 KNOWCAP_{it} * BUREAU_{it} + \gamma Z_{it} + \alpha_i + \delta_t + \varepsilon_{it} \quad (3)$$

from which we can derive the average causal effect of $BUREAU$ on the dependent variable *INN*, for given values of $KNOWCAP$.

While bureaucracies tend to be rule-bound and hence slow to change, some may nevertheless raise the possibility of reverse causality, implying that $Cov(BUREAU_{it}, \varepsilon_{it}) \neq 0$. We address this aspect using the control function method (Heckman 1976; Blundell and Powel 2004; Imbens and Wooldridge 2007). Variable $BUREAU_{it}$ is first regressed on instrument(s) I_{it}, conditioning on Z_{it}, to derive the residuals $\widehat{\omega}_{it}$. These residuals then reflect the effect of all omitted variables on $BUREAU_{it}$, including that of innovation PAT_PC_{it}, if any. Using these residuals, we augment equation (3) to obtain:

$$PAT\_PC_{it} = \beta_1 BUREAU_{it} + \beta_2 KNOWCAP_{it} * BUREAU_{it} + \gamma Z_{it} + \lambda \widehat{\omega}_{it} + \alpha_i + \delta_t + u_{it} \quad (4)$$

Since $\widehat{\omega}_{it}$ includes the reverse causal effect of PAT_PC on $BUREAU$, if any, the error term in equation (4) is now purged of this previously omitted variable. As a result, $u_{it} \perp (BUREAU_{it}, \widehat{\omega}_{it})$, so that the parameter estimates, or the so-called control function estimates, can now be obtained by estimating this relationship in the 'normal' manner. Evidently, insignificance of parameter λ will indicate insignificance of the reverse causal effect.

3. The Model Variables and Data Employed

To study the relationship between the innovation output of a country and its bureaucratic performance, we use country-level panel data. Given that the data on bureaucratic performance as captured in our study are only available from 2004 onwards, and discarding cases where observations are missing for the regressors, our sample is an unbalanced panel of 42 countries[4] spanning the period 2004-2018.

3.1 *The Treatment Variable or Bureaucratic Performance*

The 'treatment variable' in this analysis is bureaucratic performance, denoted $BUREAU$ in specification (4) above, which we first discuss and then define in the context of our study. Weber (1968) opined that "bureaucracy can be structured to stimulate economic growth". Efficient bureaucratic structure, he argued, could be engendered by following rule-based processes, having entry exams, and by building-in high status, rank-based salary and substantial tenure for personnel. Although this may well be possible, a positive outcome is not quite the norm across nations. While some countries may possess the resources to pay their civil servants well, others may not. While some countries may be able to balance a long tenure period with adequate provisions to ease out the non-performers, others may not be able to achieve that. As a result, public bureaucracies in general have acquired the reputation of being relatively inefficient. This is often ascribed to a weak (monetary) incentive structure, excessive security of tenure, and insufficient internal competition (Côté 2012). Furthermore, numerous studies inform us that civil servants are often only concerned about themselves – their power, designation, salaries, postings, etc., and may not be adequately concerned about the interests of the people they are supposed to serve (Dixit 2012).[5] In short, bureaucracy can be very inefficient, and it can actually hinder innovation and investment in the economy, and slow down growth.

Much of the received literature that we reviewed earlier in the paper, strives to capture bureaucratic quality and efficiency in terms of various aspects of bureaucratic *capacity*, such as professionalism and openness to external talent. A professional administrative service is one founded on competitive, meritocratic hiring, and merit-based promotions (Evans and Rauch 1999), and is apolitical in nature. Consequently, the administrative officers may be taken to possess the requisite skills. Moreover, it is claimed, they would not be politically partisan, and would presumably handle public policies on merit even when their own political leanings do not accord with those of the incumbent government. Furthermore, career bureaucrats may be expected to adopt a long(er)-term perspective on issues, unlike political appointees whose shorter tenure robs them of a long run perspective on various matters. In the longer run, therefore, greater professionalism makes for greater efficiency of performance. With regard to the second important aspect of bureaucracy or its openness to external talent, if all placements happen from within the cadres, the selection of officers will tend to be based on familiarity, networking, and conformity to institutional norms (Teodoro 2009), which would limit internal competition. By contrast, personnel that are drawn from other domains tend to be less conforming and more risk-taking and, therefore, are more conducive to innovation in the spheres that the bureaucracy serves, including science and technology policy. The lateral movement of personnel would also promote internal competition, and goad individuals to outperform their peers.

However, analyses employing such measures have several limitations. Research shows that a variety of structural configurations can generate the conditions considered conducive for innovation (Nord and Tucker 1987; Dougherty and Corse 1995), implying that different bureaucratic structures could result in similar innovation outcomes. Thus, higher salaries in one country and better entrance exams in another may both result in an equally meritocratic bureaucracy and, therefore, similar innovation outcomes. Secondly, one must realise that it is not just a question of engendering a given bureaucratic structure in a given milieu/country, but that of also creating a certain value system (Dougherty and Corse 1995); and this may not necessarily follow by mechanically implanting a structure obtaining in a given milieu into another. Furthermore, it is important to emphasize that the variables discussed above merely serve to capture bureaucratic *capacity* or what bureaucracy *could* deliver, and do not necessarily reflect bureaucratic performance per se or what bureaucracy *actually* delivers. Evidently, for our purpose, measures of the latter are preferable to those of the former, since the proof of the pudding is in the eating. Implicit in the concern for bureaucratic performance are concerns relating to delays in bureaucratic decision-making (which may be proxied by delays regarding matters such as construction permits, electricity connections, property registration, credit purveyance, etc.), as well as the cost of various projects (which may be proxied by the number of procedures required for getting a project off the ground, and so on); so that differences in bureaucratic performance across space and time would reflect differences in one or more of these underlying factors. Such differences would inevitably have domino effects, and could arguably be crucial in determining the magnitude and quality of innovation in an economy.

We represent (actual) bureaucratic performance ($BUREAU$) by the ease of doing business score, which attempts to quantify regulatory quality and efficiency (World Bank 2019). It is measured as the unweighted mean of ten sub-indices pertaining to the procedures, time and cost of launching a business venture, acquiring a construction permit, procuring an electricity connection, registering property, securing credit, protecting minority investors, paying taxes, trading across international borders, enforcing contracts, and resolving insolvency claims (World Bank 2019). The score ranges from 0 to 100, with larger scores indicating better performance.

3.2 *The Confounders*

To complete the model specification, we now discuss the confounders or control variables in our study. The primary inputs into innovation are the material and human resources that a country devotes to innovative activity (for example, Mairesse and Mohnen 2005). Since the accumulation of such resources is of relevance, we measure this resource input in terms of the stock of knowledge capital, which we compute from the flow of research and development (r&d) investment. The r&d expenditures are drawn from World Development Indicators (World Bank 2022), and include both capital and current expenditures in the areas of basic research, applied research, and experimental development, in the business enterprise, government, higher education and private non-profit sectors.[6] Since the current expenditure component of r&d investment typically pertains to the expenditure made on hiring scientists, engineers, and technicians, we do not need to separately include such personnel in our specification.[7] We first convert the r&d data into PPP$ magnitudes, to facilitate cross-country comparability over space and time. We then construct the stock of knowledge capital using the perpetual inventory relationship (Hall 1990, Kanwar and Hall

2017) $K_{Kt} = (1-\delta)K_{K(t-1)} + RD_t$, where K_K denotes the knowledge capital stock, RD denotes research and development expenditure, δ represents the depreciation rate of knowledge capital, and t indicates the time period. To derive the value of the knowledge capital stock in the 'first' period, we divide the r&d investment in that period by the sum of the depreciation rate of knowledge capital (δ) and the pre-sample growth rate of r&d, where the latter is proxied by the growth rate of r&d over roughly 2000-2018. We follow the received literature (Hall 1990) in employing a depreciation rate for knowledge capital of 15% per annum, which gives us regressor $KNOWCAP$.

A more comprehensive assessment of the research potential of a country would suggest inclusion of education measures. Education not only develops the intrinsic research capability, but also augments the ability to absorb technology (including that developed elsewhere), and build upon it (Leiponen 2005; see also Baumol 2005 for some unorthodox views and evidence in this regard). We capture this human capital dimension of an economy in terms of the percentage population with secondary education ($PPOPSEC$). Using Barro-Lee (2013) quinquennial data till 2010 (the last year for which it is available), and their quinquennial projections for the remaining years of our sample period (Barro-Lee 2015), we derive the annual data series for this variable on the premise of proportionate change between quinquennial endpoints.

Technology imports may contribute to the domestic innovation effort, both directly by providing the requisite input into domestic technology projects, as well as indirectly by enhancing a country's overall technological capability (Kanwar 2012). We proxy this factor ($TECH\_IMP\_PC$) by payments made by the residents of a country to non-residents for the use of intellectual property, per capita (World Bank 2022). The intellectual property comprises patents, industrial designs, layout designs of integrated circuits, trademarks, service marks, and copyrights, as well as the operation of franchises via licensing. Although the payments for trademarks, service marks, and sometimes copyrights, do not necessarily involve technology transfer, existing data do not permit disaggregation by type of intellectual property. Nor do the data permit a correction for possible transfer pricing for technology transferred from parent multinationals to their subsidiaries.

In addition to technology purchased from abroad, a country may also benefit from international spillovers of technical knowhow (Madsen 2007; Connolly 2003; Coe and Helpman 1995). A major conduit of such spillovers are imports of goods from trade partners, embodying the improvements in technology in those countries. These goods may contribute to innovation in the importing country both as direct inputs into technology production, as well as via reverse engineering. We proxy this factor by a country's high-tech commodity imports per capita ($HTCOMM\_IMP\_PC$),[8] computed using online data (UN COMTRADE 2022).[9]

Imported goods as a whole, however, play a more complicated role vis-à-vis domestic innovation. By increasing domestic competition, they exert a downward pressure on domestic prices and the profits of domestic firms, which may induce the survivor domestic firms to either become more innovative (see, for instance, the evidence provided by Bloom et al. 2016, Keller 2002, Bernstein and Mohnen 1998, and Coe and Helpman 1995), or indeed less innovative (as shown by Autor et al. 2020). The effect of exports on domestic innovation is similarly nuanced. Thus, Smith (2014) demonstrates that exporting encourages domestic innovation in both relatively leading and lagging industries when foreign stocks of knowledge are large (implying high potential competition), but discourages innovation in the relatively lagging industries when knowledge abroad is at lower levels (implying lower potential competition). In addition to trade, a relatively open economy may also imply foreign direct investment inflows as well as r&d by recipient-country multinational affiliates, both of which might bring in technology. Therefore, along with the inflow of high-tech commodities mentioned in the previous paragraph, we also consider an economy's openness as a whole. We represent an economy's openness to trade and investment flows ($OPENNESS$) using the so-called 'Area-4' sub-index of the Economic Freedom dataset (Economic Freedom 2021). This index encapsulates numerous aspects of the "freedom to trade internationally" such as tariff barriers, non-tariff barriers, black market exchange rates, foreign ownership and investment regulations, and capital restrictions. This index ranges from 0 to 10, with larger values implying greater freedom to trade and invest internationally.

There appears to be some evidence that domestic innovation is incentivised by stronger intellectual property rights (Branstetter, Fisman and Foley 2006; Chen and Puttitanum 2005). We proxy the strength of intellectual property protection in an economy (IPR) by the modified Ginarte-Park index of patent rights. The Ginarte-Park index (Ginarte and Park 1997; Park 2008) is a de jure index which incorporates five aspects of patent protection – coverage, duration, membership of certain international organisations, provisions to prevent revocation of protection once granted, and some statutes pertaining to enforcement of these rights. The indices for these aspects range from 0 to 1, and their unweighted sum is the Ginarte-Park index. Using the fact that this index increases steadily over time for the sample countries (with few fluctuations), we convert the quinquennial series into an annualized series assuming proportional growth in the intervening years. We then strengthen this measure by including another sub-index to capture the implementation dimension of such property rights. The (annual) implementation index due to Papageorgiadis and Sofka (2020) is based on three categories of property rights implementation costs – namely, servicing costs, property rights protection costs, and monitoring costs. Since it ranges from 0 to 10, we divide it by 10 to make its range 0 to 1, and then add it to the annualized Ginarte-Park series. This gives us the intellectual property rights variable IPR for our study, which ranges from 0 to 6, with larger values indicating stronger protection.

On the basis of the above discussion, our preferred specification is:[10]

$$Ln\ PAT\_PC_{it} = \beta_1 BUREAU_{it} + \beta_2 KNOWCAP * BUREAU_{it} + \beta_3 PPOPSEC_{it} + \beta_4 TECH\_IMP\_PC_{it} + \beta_5 HTCOMM\_IMP\_PC_{it} + \beta_6 OPENNESS_{it} + \beta_7 IPR_{it} + \alpha_i + \delta_t + \varepsilon_{it} \quad (5)$$

where all variables have already been defined, α_i are the country fixed effects (relating to variables such as research ethos, scientific temperament in the society at large, work attitudes, factor endowments, etc.), γ_t are the year fixed effects (relating to variables such as the international economic climate, international economic shocks such as the 2008 stock market collapse, and the like), and ε_{it} are the idiosyncratic errors.

To address the possibility that $Cov(BUREAU_{it}, \varepsilon_{it}) \neq 0$ on account of reverse causality, we employ the control function approach as follows.

3.3 *Estimating the control function variable*

We exploit the fact that the treatment variable $BUREAU$ is strongly associated with the Government Effectiveness index from the Worldwide Governance Indicators dataset (Kaufman, Kraay and Mastruzzi 2010). This index coalesces perceptions pertaining to the quality of public services, the quality of the civil service, the quality of policy formulation and implementation, and the government's credibility of its commitment to such policies. These subjective assessments were obtained from surveys of firms, households, commercial business information providers, non-government organisations, multilateral organisations, and various public-sector entities. Note that the quality of public services, the quality of the civil service, and other elements that constitute the government effectiveness index $GOVEFF$, in turn translate into the number of procedures, time and cost of various activities (such as starting a business, registering property, obtaining credit, etc.) that underlie the treatment variable $BUREAU$. In other words, variable $GOVEFF$ influences the outcome variable PAT_PC via the treatment variable $BUREAU$. Secondly, for our sample, $Cov(GOVEFF,\ BUREAU) = 0.8017$. Thirdly, estimating equation (5), we find that $Cov(GOVEFF, \hat{\varepsilon}_{it}) \approx 0$, or more precisely 0.0128. For these reasons, $GOVEFF$ is a valid instrument for the treatment variable $BUREAU$.

Regressing $BUREAU_{it}$ on instrument $GOVEFF_{it}$, conditioning on the confounders Z_{it} and the country and year fixed effects, we derive the residuals $\widehat{\omega}_{it}$.[11] Including these as an additional regressor in (5), we get our final estimation equation:

$$Ln\ PAT\_PC_{it} = \beta_1 BUREAU_{it} + \beta_2 KNOWCAP * BUREAU_{it} + \beta_3 PPOPSEC_{it} + \beta_4 TECH\_IMP\_PC_{it} + \beta_5 HTCOMM\_IMP\_PC_{it} + \beta_6 OPENNESS_{it} + \beta_7 IPR_{it} + \lambda\widehat{\omega}_{it} + \alpha_i + \delta_t + u_{it} \qquad (6)$$

where the term $\widehat{\omega}_{it}$ controls for any possible reverse causal effect of PAT_PC on $BUREAU$, as explained in section 2 above.[12]

Table 1 presents the summary statistics for our variables, both the regressands and regressors used in the various regressions, as well as some others which might facilitate interpretation of the estimation results discussed in the sections below. The table also reports the coefficients of correlation between the regressors. Although the latter suggest multi-collinearity between some regressors, we are able to manage that by orthogonalizing the regressors in question (more on that below), which does not alter the magnitude, sign or significance of the 'treatment variable' $BUREAU$ in any manner.

4. Empirical Results

4.1 *The 'baseline' results*

The 'baseline' results are presented in Table 2, column (1). The hypothesis that the slope coefficients are identically 0 is strongly rejected at the 1% significance level. The control function variable $\hat{\omega}$ is insignificant, indicating the absence of reverse causality. The results reveal the strong significance of bureaucratic performance, as brought out by the joint significance of variables $BUREAU$ and $KNOWCAP * BUREAU$ at less than the 1% level, in explaining variations in total patent applications per capita. The estimated coefficients indicate, that a one-unit improvement in bureaucratic performance ($BUREAU$) raises the number of *total patent applications* of a sample country by about 1813, at the sample median of the knowledge capital stock ($KNOWCAP$). This is a substantial change, which is 5.0% of the sample mean of total patent applications. Furthermore, the effect of a unit increase in bureaucratic efficiency is heterogenous. Thus, at the 95th percentile of the knowledge capital stock, a one-unit increase in bureaucratic efficiency raises total patent applications of a sample country by 2329 (compared to 1813 at the median level or 50th percentile), which is about 6.5% of the sample mean patent applications. In other words, at the 95th percentile of the knowledge capital stock as opposed to the 50th percentile, the effect of a unit increase in bureaucratic efficiency in raising innovation is about 28% larger.

Of the control variables, the ones that stand out are human capital or the percentage population with secondary education ($PPOPSEC$), and high-tech imports ($HTCOMM\_IMP\_PC$), both of which are mildly significant, indicating the importance of the education input in the innovation process as well as that of international spillovers.

4.2 *Disaggregating total patent applications by technology group*

The patent applications considered in the above empirical exercises belong to several different technology categories. It would be re-assuring to know that the significance of bureaucratic performance vis-à-vis innovation obtains across several if not all categories of technology, rather than being driven by some lone technology group. To explore this issue, we categorize WIPO's technology classes (World Intellectual Property Organization 2022; Schmoch 2008) into five technology groups, which are intensive in intellectual property, and for which patents are supposedly important instruments of appropriation (Cohen, Nelson and Walsh 2000). These technology groups are: Group 1 – Electrical/Electronics Technology, Group 2 – Professional and Scientific Equipment, Group 3 – Pharmaceuticals, Group 4 – Chemicals, and Group 5 – Machinery (Non-electrical). The detailed composition of each group is provided in the Appendix. We then compute the patent applications for each of our five technology groups, using WIPO data for the technology classes comprising each group. Normalising by population gives us the per capita figures for each group, and the regressands so-derived are named PAT_PC_GP1, PAT_PC_GP2, PAT_PC_GP3, PAT_PC_GP4, and PAT_PC_GP5.[13]

The regressions estimated using these dependent variables are reported in columns (2) to (6) of Table 2. The control function variable $\widehat{\omega}$ is insignificant in all five regressions, indicating the unimportance of reverse causality. In all five regressions, the bureaucratic performance terms, $BUREAU$ and $KNOWCAP * BUREAU$, turn out to be jointly strongly significant at around the 1% level or less, in explaining variations in national innovation. Of the confounder variables, high-tech commodity imports continue to be of interest, and the intellectual property rights index is positive significant in four of the five regressions. Using the coefficient estimates of the 'causal terms' from columns (2) to (6) of Table 2, we find that at the 50th percentile of the knowledge capital stock, a one-unit improvement in bureaucratic performance is associated with an increase of 995 patent applications for group 1, 885 for group 2, 435 for group 3, 666 for group 4, and 547 for group 5. These are substantial increases, amounting to 6.1%, 11.7%, 19.8%, 13.5%, and 13.3%, of the sample mean patent applications for the respective groups.

As with the total patent applications per capita, these group-wise responses become larger at higher levels of the knowledge capital stock. Thus, at the 95th percentile of the knowledge capital stock, a one-unit increase in bureaucratic efficiency raises total patent applications of group 1 by 1309, of group 2 by 1034, of group 3 by 468, of group 4 by 789, and of group 5 by 664. These increases constitute about 8.0%, 13.7%, 21.3%, 16.0%, and 16.1%, respectively, of the sample mean patent applications of the five groups. Viewed alternatively, at the 95th percentile of the knowledge capital stock as opposed to the 50th percentile, the effect of a unit increase in bureaucratic efficiency on total patent applications is larger by about 32% for group 1, 17% for group 2, 8% for group 3, 19% for group 4, and 21% for group 5.

4.3 *Re-defining the dependent variables as patent stocks*

One might argue that instead of working with patent flows, we ought to work with patent stocks, for they represent innovation better insofar as they not only account for fresh infusions into the pool of innovations available at any given point in time, but also allow for the depreciation of this pool over time. As a robustness check, therefore, we repeat all the previous estimations, with the relevant patent stocks variables replacing the patent flows variables as dependent variables. These stock figures are computed using the perpetual inventory method outlined in section 3.3, assuming a 15% depreciation rate.

The 'baseline' results with the patent applications stock per capita (PAT_ST_PC) are presented in Table 3, column (1). Columns (2) to (6) report the regression results using as regressands the patent applications stock per capita by technology group, i.e., $PAT\_ST\_PC\_GP1$ to $PAT\_ST\_PC\_GP5$. The control function variable $\widehat{\omega}$ is insignificant in all regressions, consistent with the absence of reverse causality. In conformity with the results in Table 2, we find that bureaucratic performance has a strongly significant positive influence on the patent applications stock per capita, both for innovations in the aggregate as well as for innovations disaggregated across the five technology groups. The coefficients of the 'causal terms' are roughly in the same range as before, and there appears to be no gain in repeating the quantitative implications.[14] Of the control variables, the education variable, high-tech commodity imports, and the strength of intellectual property rights also appear significant across the regressions.

4.4 *Re-defining $\beta(.)$ as a nonlinear function*

To counter the possibility of misspecification bias, we redefine $\beta(.)$ as the quadratic function $\beta * (a + bX_{it} + cX_{it}^2)$, so that the estimating equation becomes

$$Ln\ PAT\_PC_{it} = \beta_1 BUREAU_{it} + \beta_2 KNOWCAP * BUREAU_{it} + \beta_3 KNOWCAP^2 * BUREAU_{it} + \beta_4 PPOPSEC_{it} + \beta_5 TECH\_IMP\_PC_{it} + \beta_6 HTCOMM\_IMP\_PC_{it} + \beta_7 OPENNESS_{it} + \beta_8 IPR_{it} + \lambda\widehat{\omega}_{it} + \alpha_i + \gamma_t + u_{it} \quad (7)$$

We re-do all the regression exercises along the lines of Table 2 (where the dependent variables appear as flows) and Table 3 (where the dependent variables appear as stocks), but with the extra term in specification (7), i.e., $KNOWCAP^2 * BUREAU_{it}$. The results are presented in Tables 4 and 5.

Suffice it to note that our conclusions remain unaltered. Specifically, the regressors $BUREAU_t$, $(KNOWCAP * BUREAU)_t$ and $(KNOWCAP^2 * BUREAU)_t$ remain jointly strongly significant in explaining variations in innovation outcomes variously defined, i.e., both in the aggregate as well as disaggregated by technology group. (Although, these variables are insignificant for group 3 flows, they are weakly significant for group 3 stocks.) Additionally, the semi-elasticities associated with the nonlinear specification of $\beta(.)$, which inform us about the increase in patent applications for a unit increase in variable $BUREAU$, are in the same range as those reported previously for the linear specification of $\beta(.)$.

5. Conclusions

This paper attempts to explore an important fragment of the bureaucracy-growth jigsaw, by bringing to the fore the relationship between bureaucratic performance and innovation. Since government bureaucracy plays an important role in provisioning the incentives, resources and motivation for innovative activity, bureaucratic inefficiency tends to mitigate this contribution indirectly (by raising costs and diverting resources from the innovation effort) as well as directly (by hurting incentives and lessening motivation).

Using an unbalanced panel of countries spanning the period 2004-2018, we find unambiguous and strong support for the contention that better bureaucratic performance encourages innovation, ceteris paribus. Our estimates suggest that a unit improvement in bureaucratic performance raises total patent applications by economically significant amounts. Further, this response is heterogenous, and varies positively with the level of the knowledge capital stock that a country owns. Furthermore, this effect is not driven by just one or two technology groups, but is broad-based and appears to hold across all the technology-intensive industry groups. Our results are robust to several pertinent variations in the model specification. Taken together, the empirical results strongly confirm the lay wisdom that improvements in bureaucratic performance, via a decrease in the relevant procedures, time and cost, would likely benefit innovation, which is a key input into the process of modern economic growth.

Appendix

On the basis of the technology classification of patents proposed to (and adopted by) the World Intellectual Property Organization by Schmoch (2008), we compose five groups of technologies, which are intensive in intellectual property and for which patents are supposed to be important instruments of appropriation (Cohen, Nelson and Walsh 2000). These technology groups are defined below.

Group 1: Electrical/Electronics Technology – Electrical machinery, apparatus, energy; Audio-visual technology; Telecommunications; Digital communication; Basic communication processes; Computer technology; IT methods for management; Semiconductors.

Group 2: Professional and Scientific Equipment – Optics; Measurement; Control; Medical technology.

Group 3: Pharmaceuticals – Pharmaceuticals.

Group 4: Chemicals – Organic fine chemistry; Macromolecular chemistry, polymers; Basic materials chemistry; Surface technology, coating.

Group 5: Machinery (Non-Electrical) – Engines, pumps, turbines; Textile and paper machines; Other special machines.

Having defined these five technology groups, we then compute the total patent applications in each group for each of our sample countries.

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Table 1: Descriptive Statistics

Variable	Units	Mean	Median	Standard Deviation	Minimum	Maximum
PAT	Count	36097.91	1646.5	127764	33.00	1393815
PAT_PC	Count	0.0002820	0.0001242	0.0005685	1.81e-06	0.0032789
PAT_PC_GP1	Count	0.0002328	0.0000530	0.0003779	2.31e-07	0.0017859
PAT_PC_GP2	Count	0.0001233	0.0000451	0.0001744	4.56e-08	0.0009127
PAT_PC_GP3	Count	0.0000487	0.0000248	0.0000912	4.53e-08	0.0006564
PAT_PC_GP4	Count	0.0000808	0.0000296	0.0001270	7.60e-08	0.0008583
PAT_PC_GP5	Count	0.0000667	0.0000334	0.0000864	6.80e-08	0.0003778
PAT_ST_PC	Count	0.0018263	0.0007671	0.0036435	8.72e-06	0.0217877
$PAT\_ST\_PC\_GP1$	Count	0.0013641	0.0003971	0.0022384	6.06e-07	0.0099477
$PAT\_ST\_PC\_GP2$	Count	0.0007001	0.0003108	0.0009693	4.12e-07	0.0049864
$PAT\_ST\_PC\_GP3$	Count	0.0003079	0.0001476	0.0005066	2.00e-07	0.0032767
$PAT\_ST\_PC\_GP4$	Count	0.0004995	0.0001791	0.0007357	1.85e-07	0.0042422
$PAT\_ST\_PC\_GP5$	Count	0.0004269	0.0002695	0.0005553	4.15e-07	0.0023655
$BUREAU$	Index	73.00	74.88	10.42	27.56	91.33
$KNOWCAP$	Bn PPP$	21177.29	4985.56	49254.78	205.51	327988.40
$PPOPSEC$	Percentage	55.99	56.41	13.91	26.88	88.17
$TECH\_IMP\_PC$	PPP$	265.14	98.28	618.89	0.54	4349.34
$HTCOMM\_IMP\_PC$	PPP$	1433.09	997.58	2314.19	8.35	18013.65
$OPENNESS$	Index	7.75	8.00	0.96	3.14	9.56
IPR	Index	4.77	4.84	0.63	2.77	5.83
POP	Count	1.11e+08	3.17e+07	2.81e+08	318041	1.39e+09

Correlation Coefficients

	$BUREAU$	$KNOWCAP$	$PPOPSEC$	$TECH\_IMP\_PC$	$HTCOMM\_IMP\_PC$	$OPENNESS$	IPR
$BUREAU$	1.00						
$KNOWCAP$	0.14	1.00					
$PPOPSEC$	0.04	–0.06	1.00				
$TECH\_IMP\_PC$	0.33	–0.08	–0.03	1.00			
$HTCOMM\_IMP\_PC$	0.42	–0.06	–0.02	0.85	1.00		
$OPENNESS$	0.65	–0.01	0.23	0.35	0.43	1.00	
IPR	0.63	0.31	0.28	0.29	0.31	0.66	1.00

Notes: PAT = patent applications;
PAT_PC = patent applications per capita; $PATINT$ = patents (international);
PAT_PC_GPj = patent applications per capita in technology group j (j = 1, …, 5);
$PAT\_\_ST\_PC$ = patent applications stock per capita;
$PAT\_ST\_PC\_GPj$ = patent applications stock per capita in technology group j (j = 1, …, 5);
$EASE$ = ease of doing business index; $KNOWCAP$ = knowledge capital stock assuming 15% depreciation (PPP$);
$PPOPSEC$ = percentage population with secondary education; $TECH\_IMP\_PC$ = technology imports per capita;
$HTCOMM\_IMP\_PC$ = high-technology commodity imports per capita;
$OPENNESS$ = openness to trade and investment index; IPR = intellectual property rights index; POP = population.

Table 2: Innovation Flows and Bureaucratic Performance – Linear Causal Effect

	Dependent Variable Aggregate	Dependent Variable Disaggregated by Technology Group				
Regressor	PAT_PC	PAT_PC_GP1	PAT_PC_GP2	PAT_PC_GP3	PAT_PC_GP4	PAT_PC_GP5
	(1)	(2)	(3)	(4)	(5)	(6)
$BUREAU$	0.0571†	0.0379	0.0641*	0.0801†	0.0735*	0.0732*
	(0.0343)	(0.0355)	(0.0368)	(0.0529)	(0.0376)	(0.0407)
$KNOWCAP * BUREAU$	1.66e-07***	1.22e-07***	1.10e-07**	6.19e-08***	1.39e-07***	1.58e-07***
	(2.80e-08)	(3.08e-08)	(4.48e-08)	(2.27e-08)	(3.86e-08)	(4.30e-08)
$PPOPSEC$	0.0140*	0.0177*	0.0116	0.0091	0.0111	0.0054
	(0.0076)	(0.0091)	(0.0125)	(0.0095)	(0.0101)	(0.0105)
$TECH\_IMP\_PC$	0.0812	–0.0450	0.0072	0.1532	0.1739*	0.1083†
	(0.0820)	(0.0748)	(0.0816)	(0.1275)	(0.0982)	(0.0801)
$HTCOMM\_IMP\_PC$	0.0231*	0.0037	0.0112	0.0524**	0.0394†	–0.0025
	(0.0137)	(0.0207)	(0.0359)	(0.0216)	(0.0283)	(0.0157)
$OPENNESS$	0.0148	0.1118	0.0782	–0.0352	0.0261`	–0.0985
	(0.1352)	(0.1305)	(0.1702)	(0.2138)	(0.1778)	(0.1511)
IPR	0.0352	0.1629**	0.2535**	0.0806	0.1911*	0.1122†
	(0.0854)	(0.0756)	(0.1158)	(0.1227)	(0.1071)	(0.0734)
$\hat{\omega}$	–0.0386	–0.0174	–0.0522	–0.0626	–0.0611	–0.0654
	(0.0328)	(0.0364)	(0.0358)	(0.0550)	(0.0375)	(0.0394)
Intercept	–14.2380***	–14.1180***	–15.8328***	–17.5433***	–16.6436***	–16.4579***
	(2.3250)	(2.1964)	(2.0800)	(3.5272)	(2.3857)	(2.4053)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
P-value (all slopes 0)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P-value: $BUREAU = KNOWCAP * BUREAU = 0$	0.0000	0.0005	0.0112	0.0087	0.0004	0.0002
$\bar{R}^2$	0.4089	0.4756	0.5233	0.2237	0.3160	0.4087
N*T	592	592	592	592	592	592

Notes: Clustered robust standard errors in parentheses below the coefficients;
***, ** and * denote significance at the 1%, 5% and 10% levels, using a two-tail test;
† denotes significance at the 10% level using a one-tail test

Table 3: Innovation Stock and Bureaucratic Performance – Linear Causal Effect

Regressor	Dependent Variable Aggregate	Dependent Variable Disaggregated by Technology Group				
	PAT_ST_PC	$PAT\_ST\_PC\_GP1$	$PAT\_ST\_PC\_GP2$	$PAT\_ST\_PC\_GP3$	$PAT\_ST\_PC\_GP4$	$PAT\_ST\_PC\_GF$
	(1)	(2)	(3)	(4)	(5)	(6)
$BUREAU$	0.0522†	0.0360	0.0591†	0.0684*	0.0513†	0.0274
	(0.0374)	(0.0378)	(0.0357)	(0.0373)	(0.0332)	(0.0326)
$KNOWCAP * BUREAU$	1.78e-07***	1.30e-07***	1.43e-07***	6.38e-08***	1.07e-07**	1.68e-07***
	(2.58e-08)	(2.69e-08)	(4.18e-08)	(2.10e-08)	(4.62e-08)	(4.16e-08)
$PPOPSEC$	0.0190**	0.0233**	0.0150†	0.0121†	0.0157†	0.0213**
	(0.0078)	(0.0092)	(0.0101)	(0.0097)	(0.0097)	(0.0084)
$TECH\_IMP\_PC$	0.0160	0.0099	0.1432*	0.1629*	0.1579*	0.0578
	(0.0875)	(0.0771)	(0.0734)	(0.0912)	(0.0885)	(0.0859)
$HTCOMM\_IMP\_PC$	0.0121	0.0274†	0.0450†	0.0504**	0.0609**	0.0287**
	(0.0131)	(0.0197)	(0.0302)	(0.0206)	(0.0227)	(0.0116)
$OPENNESS$	0.0261	0.1865	0.0622	0.0667	0.1496	0.1597
	(0.1482)	(0.1435)	(0.1382)	(0.1603)	(0.1465)	(0.1362)
IPR	0.0234	0.1642*	0.1235†	0.1103	0.1917*	0.1317†
	(0.0912)	(0.0872)	(0.0844)	(0.0989)	(0.0974)	(0.0831)
$\hat{\omega}$	–0.0298	–0.0149	–0.0459	–0.0503	–0.0396	–0.0163
	(0.0361)	(0.0380)	(0.0352)	(0.0387)	(0.0326)	(0.0316)
Intercept	–12.3951***	–12.7145***	–14.1288***	–15.3340***	–13.8582***	–12.5603***
	(2.5959)	(2.4349)	(2.2427)	(2.5054)	(2.0636)	(2.0652)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
P-value (all slopes 0)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P-value: $BUREAU = KNOWCAP * BUREAU = 0$	0.0000	0.0022	0.0009	0.0050	0.0184	0.0005
$\bar{R}^2$	0.5061	0.6631	0.6504	0.4911	0.5485	0.6050
N*T	592	592	592	592	592	592

Notes: Clustered robust standard errors in parentheses below the coefficients;
***, ** and * denote significance at the 1%, 5% and 10% levels, using a two-tail test;
† denotes significance at the 10% level using a one-tail test

Table 4: Innovation Flows and Bureaucratic Performance – Nonlinear Causal Effect

Regressor	Dependent Variable Aggregate	Dependent Variable Disaggregated by Technology Group				
	PAT_PC	PAT_PC_GP1	PAT_PC_GP2	PAT_PC_GP3	PAT_PC_GP4	PAT_PC_GP5
	(1)	(2)	(3)	(4)	(5)	(6)
$BUREAU$	0.0540†	0.0356	0.0583†	0.0792†	0.0663*	0.0658†
	(0.0360)	(0.0360)	(0.0368)	(0.0535)	(0.0380)	(0.0413)
$KNOWCAP * BUREAU$	2.01e-07***	1.49e-07***	1.77e-07***	7.19e-08	2.22e-07***	2.42e-07***
	(5.39e-08)	(5.06e-08)	(6.10e-08)	(6.05e-08)	(5.31e-08)	(5.54e-08)
$KNOWCAP^2 * BUREAU$	–1.19e-13	–8.93e-14	–2.22e-13*	–3.33e-14	–2.76e-13**	–2.80e-13**
	(1.11e-13)	(1.04e-13)	(1.25e-13)	(1.44e-13)	(1.14e-13)	(1.15e-13)
$PPOPSEC$	0.0137*	0.0175*	0.0112	0.0091	0.0105	0.0048
	(0.0076)	(0.0092)	(0.0126)	(0.0096)	(0.0100)	(0.0104)
$TECH\_IMP\_PC$	0.0773	–0.0480	–0.0002	0.1521	0.1647*	0.0089
	(0.0821)	(0.0743)	(0.0808)	(0.1274)	(0.0975)	(0.0801)
$HTCOMM\_IMP\_PC$	0.0238*	0.0042	0.0126	0.0526**	0.0411†	–0.0008
	(0.0138)	(0.0210)	(0.0367)	(0.0217)	(0.0291)	(0.0163)
$OPENNESS$	0.0160	0.1127	0.0804	–0.0348	0.0289	–0.0957
	(0.1364)	(0.1310)	(0.1713)	(0.2141)	(0.1761)	(0.1496)
IPR	0.0367	0.1641**	0.2563**	0.0810	0.1946*	0.1157†
	(0.0859)	(0.0762)	(0.1174)	(0.1228)	(0.1072)	(0.0733)
$\widehat{\omega}$	–0.0364	–0.0158	–0.0482	–0.0620	–0.0562	–0.0604
	(0.0339)	(0.0366)	(0.0358)	(0.0553)	(0.0377)	(0.0397)
Intercept	–14.0368***	–13.9668***	–15.4561***	–17.4868***	–16.1767***	–15.9831***
	(2.4424)	(2.2403)	(2.0802)	(3.5777)	(2.4210)	(2.4390)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
P-value: $BUREAU = KNOWCAP * BUREAU = KNOWCAP^2 * BUREAU = 0$	0.0001	0.0174	0.0174	0.2477	0.0003	0.0001
$\bar{R}^2$	0.4104	0.4756	0.5273	0.2225	0.3238	0.4184
N*T	592	592	592	592	592	592

Notes: Clustered robust standard errors in parentheses below the coefficients;
***, ** and * denote significance at the 1%, 5% and 10% levels, using a two-tail test;
† denotes significance at the 10% level using a one-tail test

Table 5: Innovation Stock and Bureaucratic Performance – Nonlinear Causal Effect

Regressor	Dependent Variable Aggregate PAT_ST_PC (1)	Dependent Variable Disaggregated by Technology Group $PAT\_ST\_PC\_GP1$ (2)	$PAT\_ST\_PC\_GP2$ (3)	$PAT\_ST\_PC\_GP3$ (4)	$PAT\_ST\_PC\_GP4$ (5)	$PAT\_ST\_PC\_GP$ (6)
$BUREAU$	0.0491	0.0319	0.0508†	0.0657*	0.0448†	0.0192
	(0.0393)	(0.0384)	(0.0361)	(0.0378)	(0.0337)	(0.0327)
$KNOWCAP * BUREAU$	2.13e-07***	1.77e-07***	2.39e-07***	9.48e-08*	1.83e-07***	2.63e-07***
	(5.07e-08)	(4.44e-08)	(4.77e-08)	(5.09e-08)	(5.99e-08)	(4.28e-08)
$KNOWCAP^2 * BUREAU$	–1.18e-13	–1.56e-13	–3.19e-13***	–1.03e-13	–2.50e-13*	–3.16e-13***
	(1.07e-13)	(9.39e-14)	(9.72e-14)	(1.24e-13)	(1.31e-13)	(8.75e-14)
$PPOPSEC$	0.0188**	0.0230**	0.0144†	0.0119	0.0152*	0.0207**
	(0.0079)	(0.0092)	(0.0101)	(0.0098)	(0.0098)	(0.0084)
$TECH\_IMP\_PC$	0.0120	0.0047	0.1325*	0.1595*	0.1495*	0.0472
	(0.0879)	(0.0768)	(0.0731)	(0.0910)	(0.0879)	(0.0852)
$HTCOMM\_IMP\_PC$	0.0128	0.0283†	0.0470†	0.0510**	0.0625**	0.0306**
	(0.0134)	(0.0201)	(0.0313)	(0.0208)	(0.0234)	(0.0120)
$OPENNESS$	0.0272	0.1881	0.0654	0.0678	0.1521	0.1629
	(0.1498)	(0.1451)	(0.1405)	(0.1608)	(0.1480)	(0.1383)
IPR	0.0248	0.1661*	0.1275†	0.1116	0.1948*	0.1357†
	(0.0920)	(0.0883)	(0.0858)	(0.0987)	(0.0983)	(0.0836)
$\widehat{\omega}$	–0.0277	–0.0121	–0.0402	–0.0485	–0.0352	–0.0107
	(0.0374)	(0.0384)	(0.0357)	(0.0391)	(0.0330)	(0.0316)
Intercept	–12.1945***	–12.4496***	–13.5883***	–15.1597***	–13.4354***	–12.0257***
	(2.7208)	(2.4829)	(2.2640)	(2.5506)	(2.0901)	(2.0523)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
P-value: $BUREAU = KNOWCAP * BUREAU = KNOWCAP^2 * BUREAU = 0$	0.0000	0.0011	0.0000	0.0834	0.0103	0.0000
$\bar{R}^2$	0.5077	0.6652	0.6616	0.4914	0.5554	0.6210
N*T	592	592	592	592	592	592

Notes: Clustered robust standard errors in parentheses below the coefficients;
***, ** and * denote significance at the 1%, 5% and 10% levels, using a two-tail test;
† denotes significance at the 10% level using a one-tail test

Endnotes

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[1] Thus, the extensive paperwork required to obtain financing in developing country public universities for attending international conferences, is well-known. Use of the national airlines, if there's one, may be mandatory, despite relatively expensive tickets, and inconvenient routes and itineraries. That this leads to an inefficient use of time and resources, and discourages innovation insofar as fewer researchers can avail of the benefit, appears to be lost on the bureaucracy.

[2] While we wish to focus on the contribution of the bureaucracy per se, it is somewhat difficult to separate the performance of the bureaucracy from that of the politicians that constitute the incumbent (central/federal and regional) governments, for the latter often initiate and guide policy 'in the large'. Nevertheless, whereas the politicians at the helm tend to enter and exit the system 'fairly' frequently (via cabinet reshuffles and elections, for instance), the bureaucracy exhibits greater continuity, especially where it comprises career bureaucrats. Further, while the 'overall ideas and direction' may stem from the politicians, the detailed policies as spelt out in the policy documents, and their implementation, fall within the domain of the bureaucrats. Consequently, the bureaucracy can be thought of independently of the politicians, and its performance evaluated as a distinct factor influencing the process of innovation in the economy.

[3] Furman, Porter and Stern (2002) show that public policy plays a significant role in building a country's innovation capacity by contributing to the availability of R&D resources, human capital, innovation incentives, etc.

[4] The sample countries are: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland,

India, Israel, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Russia, Singapore, Slovakia, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, Turkey, United Kingdom, Ukraine, United States of America.

[5] Officers of the Indian Civil Service (during the period when India was under British rule) were often lampooned for being neither civil nor servants! (The full criticism was that they were neither Indian, nor civil, nor servants. However, the fact that they were (mostly) not Indian but British does not concern us here.)

[6] Even so, R&D investment typically does not include expenditure on laboratory or workshop buildings per se, and hence underestimates the resources spent on innovation.

[7] This is useful, because data on the number of scientists, engineers and technicians are very patchy.

[8] According to SITC Revision 4, high-technology products are defined as those pertaining to aerospace, computers and office machines, electronics and telecommunications, pharmaceuticals, scientific instruments, electrical machinery, chemicals, non-electrical machinery, and armaments.

[9] Note that 'domestic spillovers' (i.e., between firms within a country) would be picked up implicitly, since we are considering innovations at the national level. Further, aggregate data have the advantage that spillovers between technological and non-technological innovations (for instance, managerial innovations) are also picked up, albeit implicitly.

[10] A log-linear specification was supported by the Akaike and Schwarz information criteria.

[11] Instrument $GOVEFF$ ranges from –2.5 to +2.5 in the original data (Kaufman, Kraay and Mastruzzi 2010). To ease interpretation, we re-scale it to lie between 0 and 100, which is the same range as that of variable $BUREAU$, which it instruments. (This is easily achieved using the relation $y = 50 + 20x$, where y is the instrument on the new scale and x is the

instrument on the old scale.) Regressing $BUREAU$ on $GOVEFF$ (re-scaled), the estimated coefficient of the latter is 0.2347, with a p-value of 0.057, indicating a strong positive relationship between the two variables. This further strengthens the credentials of $GOVEFF$ in instrumenting variable $BUREAU$.

[12] The advantage of the control function approach vis-à-vis two-stage least squares (2SLS) is, first, that it retains the original treatment variable(s) in the final estimating equation (Imbens and Wooldridge 2007), and second, it has been shown to be more efficient when the relationship estimated is nonlinear (Guo and Small 2016), as indeed we shall do in the robustness checks below.

[13] Note that the sum of the patent applications (per capita) for these five groups does not equal the total patent applications (per capita), or variable PAT_PC which we used above. One reason is that technology classes for which patents may not be important (Cohen, Nelson and Walsh 2000) are omitted, such as: Analysis of biological materials, Food chemistry, Environmental technology, Handling, Transport, Furniture, Games, Other consumer goods, Civil engineering, etc. This is appropriate, because we employ patent data as indicators of innovation output. Another reason is that the WIPO data by technology class pertain to total patents, and not necessarily patents by residents only.

[14] Additionally, all the empirical results reported thus far remained unchanged when we used a depreciation rate of 30% to compute the knowledge capital stock.