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Access to External Finance and Innovation: A Macroeconomic Perspective

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Abstract

This article takes a macroeconomic perspective in studying innovation as one of the channels by which better access to financial markets affects economic development. The GMM difference and system estimators which accommodate country specific heterogeneity, endogenous explanatory variables and measurement errors are used to study a panel of 76 countries from year 1988 to 2010. It is found that better access to external finance is a significant factor positively and rapidly influencing innovation and hence long-run economic growth. This positive effect on innovation is robust to both bank and capital market lending with the adverse effect of reduced access to finance on innovation felt disproportionately by lower income countries. However, the estimations suggest that the magnitude of the bank as opposed to capital market lending channel is greater. Moreover, an analysis of the recent financial crisis reveals that the lack of liquidity had a large role to play in reduction of innovation post-crisis.

Kewords: innovation; external finance; crises; dynamic panels

JEL Classification: C23; G1; O16; O47

1 Introduction

A large body of literature provides a theoretical basis and presents empirical evidence that better access to financial markets encourages economic devel-

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opment[1]. In analysing the channels through which better access to finance affects economic development, Grossman and Stiglitz (1980) and Merton (1987) suggest that innovation is the channel through which better access to external finance affects growth. The authors stress that better access to finance might offer firms better possibilities to innovate through reduction in asymmetric information, greater investments in new products and better corporate governance. However, Mayer-Foulkes et al. (2005) formalize this relation more explicitly with the lack of financial access creating a constraint on the country's ability to"jump to the frontier". They demonstrate that lesser financial development introduces a disadvantage of backwardness by introducing moral hazard on part of the innovator. In their framework financial development acts to enhance the absorptive capacity to master foreign technologies for the poorer countries and frees resources for richer countries to undertake particularly complex and expensive innovations. This article empirically explores this channel and investigates whether better access to external finance indeed facilitates innovation.

Using data from 76 countries from 1988 to 2010 and applying GMM panel estimators, it is found that better access to finance is a significant factor positively influencing innovation. Moreover, the estimations suggest that the effect of finance on innovation is rapidly propagating, with the effect on innovation felt within 2 years. These results are robust across a host of alternate innovation measures. Following Mayer-Foulkes et al. (2005), the statistically significant negative coefficient of the interaction term of bank credit and GDP per capita is interpreted as the effect of access to bank finance on innovation being more pronounced in developing countries. The positive finance-innovation relation is robust to both bank and capital market lending, however more so for bank lending. The magnitudes of estimated coefficients also suggests that this positive relationship mainly stems from bank as opposed to capital market lending. Specifically, estimates of short run elasticities suggest that a 10% increase in bank and capital market financing increases innovation by 1.63% and 0.41%, respectively[2]. Furthermore, in the financial crisis of 2007-2008, around 20% of the drop in innovation can be attributed to reduced supply of credit from banks and capital markets.

Recently some work at a micro level on the relationship between access to finance and innovation was done by Benfratello et al. (2008) and Ayyagari et al. (2011). The present article contributes to this literature by taking a macroeconomic viewpoint and therefore allows for the estimation of aggre-

[1]See Levine (2005) for a survey of literature.

[2]Short run elasticities are significant coefficient estimates for one year lag. For long-run elasticities, see Table 6.

gate effects. Unlike the previous studies, the current analysis incorporates multiple innovation measures, the recent liquidity crisis, capital markets and uses dynamic panel data methods to control for reverse causality, endogeneity and model the past knowledge base[3]. Taking a macroeconomic viewpoint on innovation becomes important due to the nature of innovation which is characterized by diffusion, displacement, creation and destruction of goods, services, and processes across time and industries. For example, a product innovation in one sector can increase income in that sector [through lower prices and hence increased demand] at the expense of other sectors, making sectoral micro level studies suspect. The use of aggregate data allows one to circumvent these problems to a large extent and get an overall effect of access to finance on innovation.

The rest of the paper is structured as follows: Section 2 presents the theoretical framework. The next section briefly discusses the main variables of interest and issues involved in estimating finance-innovation relationship. This follows a section on empirical methodology. Section 5 forms the crux of the article, discussing the quantitative and economic relevance of the main results before providing a macroeconomic analysis of innovation-finance relationship following the recent liquidity crisis. Section 6 discusses the robustness of the results. The final section concludes. Data description along with the descriptives, methodology of post crisis variance decompositions and the list of countries used in the study are presented in the appendices.

2 Theoretical Framework

To formalize the relationship between financial access and innovation, I begin with the Aghion and Howitt (1992) equation of productivity growth:

$$A = A_0 \rho^{\kappa} \tag{1}$$

where A represents technological levels with A_0 and ρ representing initial technological level and productivity parameter, respectively. The parameters are country and time specific i.e. A represents the technology level in country i at time t [to emphasize the main point, the subscripts are suppressed throughout]. Now, departing from endogenous growth models the equation (1) is altered to[4]:

$$A = A_0^{\chi} \rho^{\kappa} \tag{2}$$

[3]Past knowledge base is modelled by adding lagged (dependent) innovation variables.

[4]It is assumed that $\rho > 1$ and $\kappa < 1$ to abstract from explosive growth à la Jones (1995).

Hence, the technology improves from A_0 by the "innovation factor" ρ which takes the value greater than one [as in Aghion and Howitt (1992)][5]. Further, I endogenize ρ and A_0 by positing that innovation factor increases[6] with the past values of financial development (FD) and that technology level grows, depending on the past innovations i.e.

$$\rho = \beta_1 FD_{t-1} + \ldots + \beta_s FD_{t-s} = f(FD) \ and \ A_0 = \alpha_1 A_{t-1} + \ldots + \alpha_s A_{t-s} = g(A_0) \tag{3}$$

An important difference from the Aghion and Howitt (1992) which should be emphasised upon is the interpretation of A_0. Here, it is considered as the total innovations that accumulated depending on innovations from last period as opposed to exogenously determined initial technological level. This becomes possible as I do not assume a frontier technology country and hence abstract from the idea of "jump to the frontier" from initial technological level. Rather the focus is on past innovations affecting current innovation and past level of financial access affecting innovation.

Combining equations (2) and (3) gives:

$$A = g(A_0)^{\chi} f(FD)^{\kappa} \tag{4}$$

Substituting equations (3) into (4) and taking logs on both sides gives the following equation:

$$ln[A] = \chi ln[g(\alpha_1 A_{t-1} + \ldots + \alpha_s A_{t-s})] + \kappa ln[f(\beta_1 FD_{t-1} + \ldots + \beta_s FD_{t-s})] \tag{5}$$

The equation above will is estimated. χ and κ are long-run elasticities of impact of past innovations and financial access on innovations, respectively. On the other hand, α's and β's are short run elasticities. These effects are interpreted as follows. Firstly, as innovation is an expensive activity, the short run impact of financial access on innovation [β] will be interpreted as additional filing of patent applications for pipeline projects as there is a relaxation of financial constraints i.e. there is less delay in new projects to reach the market. On the other hand, the long-run impact of greater financial access [κ] would be interpreted as creation of larger number of new products [greater patent applications] due to greater financial access.

Particularly, two implications of the model are emphasised and brought to data. (i) Innovation today is dependent on past innovations [$g(A_0)$] and

[5] χ and κ are parameters that gives long-run effects of past innovations and financial access respectively, explanations to follow.

[6] Possibility of non-linear relationship is tested and rejected with the data at hand, see robustness section.

(ii) that innovation level of countries grows with the [past levels of] financial access [$f(FD)$].

3 Preliminary Analysis

The finance-innovation relationship gains additional importance in light of the recent financial crisis, where considerable amount of illiquidity was witnessed [see, Tirole (2011)]. Whether the paucity of external finance (i.e. limited credit availability from stock markets and banks) had a role to play in the sudden drop in productivity and innovation remains an open question. A simple analysis of growth rates of innovation and liquidity measures pre and post crisis is informative at this point, as simultaneous drops in these variables are suggestive of a positive structural relationship between external access to finance and innovation. The access to bank based external finance is proxied by Bank Credit[7] [credit provided to the private sector by domestic banks] and market capitalization [total value of listed companies in a country] provides the metric to gauge credit availability in capital markets[8]. Furthermore, patent applications [to the domestic patent offices], research and development expenditures, employment in knowledge intensive activities and number of researchers serve as proxies for innovation. Table 1

Table 1 Annual Growth Rates

Variables	**Average Annual Growth Rate 1988-2010**	**Annual Growth Pre-Crisis 1988-2007**	**Annual Growth Post-Crisis 2008-2010**
Patents	7.27	7.64	4.96
CreditbyBanks	7.57	7.63	6.89
Mar_Cap	36.71	42.44	0.39
GDP	2.06	2.26	0.81
Exports	6.36	6.71	1.04
RnDExp	6.53	6.80	4.98
Researchers	4.96	5.40	2.55
EmpKIA	0.17	2.04	-4.26
FDI	18.16	30.86	0.282

displaying annual growth rates of innovation and liquidity measures gives us

[7] Bank credit excludes credit to the public sector, credit to state-owned enterprises and cross claims of one group of intermediaries on another.

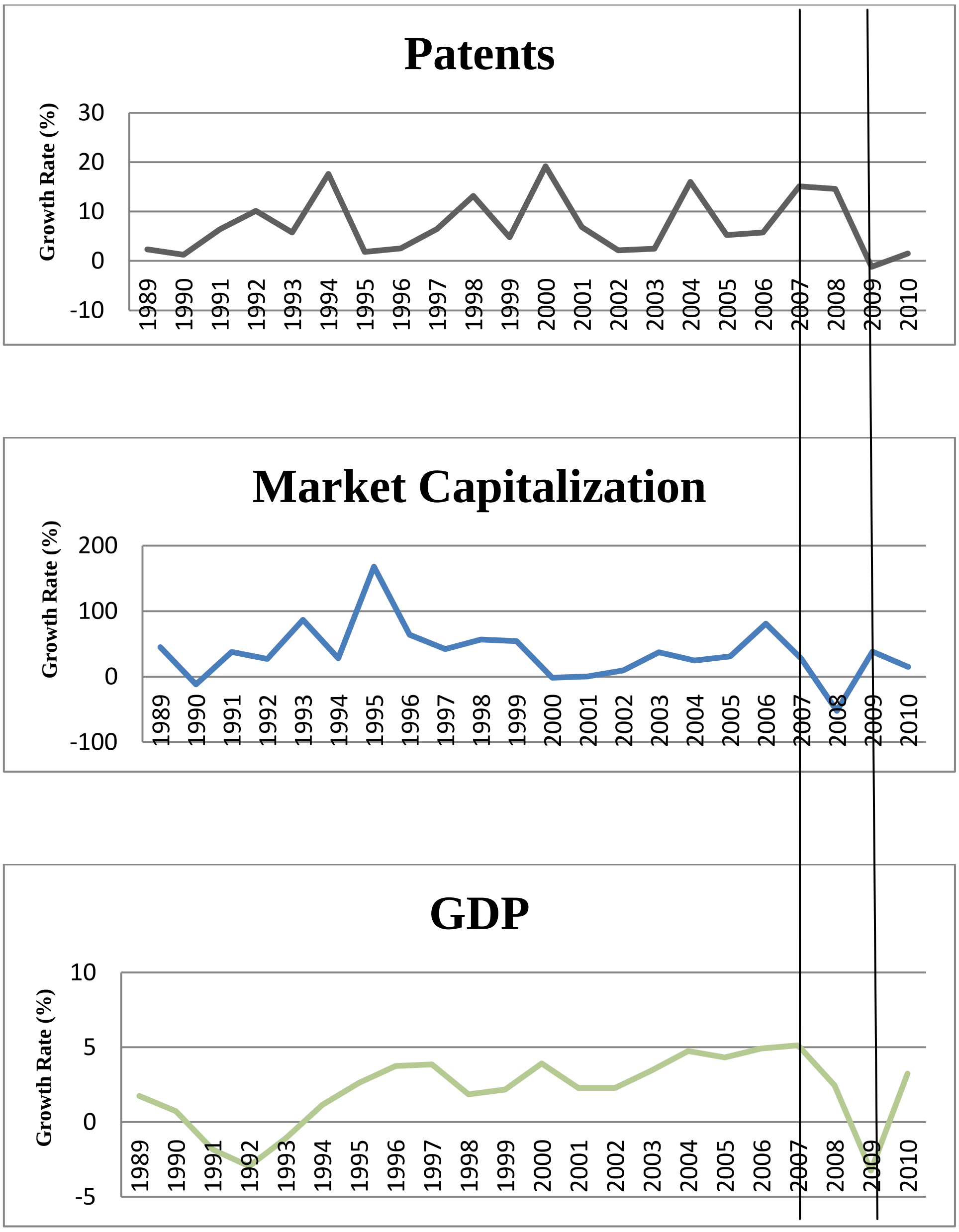
[8] The motivation and limitations of the proxies to follow.

a rough idea about whether the shock of the recent liquidity crisis had any real impact on innovation variables. The table shows a drastic reduction in market capitalization and a slow down in bank credit post-crisis. Moreover, all innovation measures see a reduction in their growth rates post crisis relative to tranquil periods. For example, average annual growth rate of patents decreased from 7.64% in tranquil period to 4.96% in the recent liquidity crisis. The growth rate of employment in knowledge intensive activities [EmpKIA] is even negative post-crisis. The sudden fall following the recent financial crisis can be taken as the first suggestive evidence for the positive relationship between finance and innovation. It is quite plausible that the recent liquidity crisis was an exogenous shock to the credit supply rather than a productivity driven demand shock. Mian and Sufi (2010) find convincing evidence for the credit supply explanation of the recent financial crisis. They find by employing household level zip code data from the United States, that the households that experienced a negative nominal income growth actually witnessed a growth in home mortgage origination. In fact, this growth in mortgages was almost twice as much compared to the group that experienced a positive income growth. Additionally, they show that the fraction of mortgages that were securitized by non-governmental sponsored enterprises (non-GSE) rose from 3% in 2002 to 20% in 2005 which resulted in a dramatic decrease in mortgage denial rates and a steep increase in debt-to-income ratios. For the 18 years they study, they document that only in the 4 years preceding the financial crisis did the income and mortgage credit growth display negative correlation. Hence, the drastic reductions of innovation post crisis is indicative of a rapidly propagating credit supply channel affecting the real economy and drying up innovations. We can grasp the sudden drop in liquidity and innovation more clearly from Figure 1 on the next page.

It becomes clear from Figure 1 that there was a drastic drop in patents and Market Capitalization following the recent liquidity crisis. Nevertheless, Bernanke and Gertler (1995) argue in their extensive study of liquidity shocks that the reduction in credit at times of crises can be completely attributed due to reduction in demand for credit. The drastic reduction in GDP as can be seen in Figure 1 adds voice to this concern as reduced private sector demand and uncertainty about the future instead of fall in external access to finance might be driving the fall in innovation.

However, this demand for credit effect being positively correlated with credit supply seem not as crucial an issue in case of innovation. Economists have long argued that innovations might in fact be concentrated at times of recessions. For example, Schumpeter (1939) reasoned that the marginal opportunity cost of forgone output at the time of economic downturns is low hence inducing agents to demand more innovations in recessions. Aghion and

Figure 1: Innovation, Market Capitalization and GDP over time



Note: The vertical lines encapsulate the recent liquidity crisis.

Saint-Paul (1998) formalizes this inter-temporal substitution effect in partial and general equilibrium models. Empirical evidence for this is documented in several studies [see for example, Blanchard et al. (1990) and Ouyang (2011)][9]. More recently, Shu (2012) compiled unique data to analyse the innovation-recession nexus more explicitly. By studying the patenting history of MIT graduates from 1980-2005, she finds that cohorts graduating during economic booms produce significantly fewer patents over the subsequent two decades than those who graduate in downturns. Hence, the estimates without demand controls [presented in Table 5] might instead show an upward bias. Nevertheless, the demand for credit effects are explicitly controlled for by including GDP and unemployment as proxies in the baseline regression.

It is also recognized that the credit variable proxies employed here, Bank Credit and Market Capitalization[10] are not primary measures of external financing and does not perfectly represent actual financing decisions of firms from bank and capital markets, respectively. For example, bank credit variable which is the total loans to the private sector provided by domestic banks is an equilibrium quantity, representing both demand and supply effects. Similarly, market capitalization do not perfectly correspond to supply of credit in the capital markets. To address this issue, demand controls in the form of GDP and unemployment are included to isolate the credit supply effects.

Moreover, there is strong empirical support that macroeconomic conditions reflect the credit availability in an economy. Hence, these secondary market indicators with demand controls, can serve as good proxies for actual credit supply available to firms. For example, Gertler and Hubbard (1993) demonstrate the relevance of the macroeconomic environment for capital market financing. Likewise, they also use aggregate income variables, specifically GNP, to account for credit demand effects. Furthermore, they show that even after controlling for firm growth opportunities, macroeconomic environment determines the time at which the firms issue equity. Korajczyk and Levy (2003) extend this line of research and provide variance decompositions of the significance of macroeconomic effects with respect to financing decisions of firms and credit availability. They show that the macroeconomic conditions affect firm capital structure choice for both financially constrained and unconstrained firms. Particularly, they find that macroeconomic environment accounts for 12% to 51% of the variation in firms leverage, 38% to

[9]Barlevy (2007) and Mayer-Foulkes et al. (2005) also documents this and emphasize that the pro-cyclical aggregate R&D series is explained by liquidity constraints where reduced supply instead of demand of credit accounts for lower aggregate R&D expenditures in recessions.

[10]See data description in Appendix A for more details on these and other variables.

48% of time-series variation in issue choice and 51% to 71% of variation in repurchases. Similarly, Baker and Wurgler (2002) using COMPUSTAT [11] firms for which IPO date could be determined also come to a similar conclusion. With a sample of around 3000 firms from 1968 to 1999, they find that even after controlling for the demand for credit, firms are more likely to issue equity when market conditions are relatively favourable. Similar evidence on positive association of general macroeconomic environment and borrowing by firms can be found in various other studies [See Kaplin and Levy (2001); Dehejia and Lleras-Muney (2003)]. Hence, market capitalization and bank credit can be expected to correlate with the supply of credit in the primary markets.

The baseline dependent variable to proxy for level of innovation is the logarithm of annual patent applications of residents in a particular country[12]. It is duly noted that theoretical notion of innovation is not easy to comprehensively capture by any single measure. For example, Schumpeter (1947) defined innovation as: "the ability to perceive new opportunities that cannot be proved at the moment at which action has to be taken, and . . . will power adequate to break down the resistance that the social environment offers to change". Similarly, the Lisbon Agenda documents of the Commission (2003) defines innovation as: "the successful production, assimilation and exploitation of novelty in the economic and social spheres" . Hence, from the onset it is noted that a measure incorporating the abstract notion of innovation is a rough estimate. Patents applications have the practical advantage of having consistent and comparable historical databases across countries. Lachenmaier and Rottmann (2011) compare patented and non-patented innovations in the German Manufacturing sector. They conclude that due to the high costs associated with patent applications, this measure adequately captures high return and important innovations. Griliches (1998) in his broad survey and analysis of patent statistics also documents the usefulness of patent applications as an indicator of innovative activity. However, the use of patent applications also has some shortcomings with the main disadvantage being that it is not an innovation output measure. Furthermore, many innovations might be missing as there might be a differences in country specific propensity to patent[13] as depending on the circumstances, secrecy

[11]COMPUSTAT is a database that covers 99,000 global securities and 99% of the world's total market capitalization with data going back to 1950.

[12]Results are unchanged for patents as a ratio of GDP, see the first column of Table 10. However, growth without scale effects literature motivated the to use non-normalized baseline innovation measure (see Appendix A for more details).

[13]Time invariant country specific propensity is controlled through differencing under the current framework.

and/or first mover advantages might be the more viable option. To address the measurement issue, multiple innovation measures, albeit with a limited sample, are utilized as part of robustness checks. These innovation measures include: R & D Expenditures as a portion of GDP, number of researchers per million people in R & D, and employment in knowledge intensive activities normalized by labour force[14]. It is noted that R & D investments instead of patents, might be hit first by a change in liquidity supply in an economy. However, the data rejects this hypothesis. Exactly like patents, the positive effect of better external access to finance on R & D is only felt after a one year lag. Due to larger dataset [both country and time dimension] and ability to capture the most important innovations, logarithm of patent applications is kept as the baseline innovation measure.

Table 2 Correlation Matrix of Innovation Measures

InnovMeasures	**Patents**	**RnDExp**	**Researchers**	**EmpKIA**
Patents	1			
RnDExp	0.7229***	1		
Researchers	0.7138***	0.9635***	1	
EmpKnowIntenAct	0.7718***	0.7706***	0.7372***	1

*** p<0.01, ** p<0.05, * p<0.1

A correlation matrix of the various innovative measures used during the course of the paper is presented in Table 2. One can see that there is strong positive and statistically significant correlation between all measures of innovation. It can also be noted that the baseline innovation measure, the logarithm of patents [Patents] is highly correlated with all innovation measures. Therefore, we can be confident that our preferred measure of innovation does at least roughly capture the level of innovation across countries and time.

It is also noted that there are many other potential candidates for explanatory variables. For example, Gong and Keller (2003) emphasize that international trade, through facilitating technological absorption and diffusion, play an important role for innovations across countries. Additionally, there is a whole body of literature providing theoretical basis for the role of human capital in promoting innovation [see, for example Nelson and Phelps (1966); Stokke (2008) for disparate channels/views]. However, once we enter

[14]See Eurostat website for details of classification of knowledge intensive activities and Appendix A for normalization details.

income levels in our equations, these measures lose their statistical significance. Tertiary enrolment, normalized by age cohort, was used to proxy for human capital accumulation. FDI and Exports, normalized by GDP, were used to proxy for intensity of international trade. This is in line with Castellacci and Natera (2011) recent analysis of dynamics of innovation systems where they study co-evolution of different innovation measures by means of a structural panel VAR. They also note that these measures only enter the innovation equation through the GDP dynamics i.e. through aggregate demand for innovations and social/economic development. Hence, these indirect measures are left out as we already include GDP per capita in the estimated equations[15].

4 Empirical Methodology

4.1 Specification and econometric issues

To estimate a cross-country equation modelling finance and innovation as a dynamic process various economic and econometric complexities need to be considered. For the ease of exposition and to emphasize the main variables under study, let us first consider a static panel model:

$$\begin{aligned}\mathrm{INNOV}_{it} = \beta_0 + \beta_1\mathrm{CI}_{it} + \beta_2\mathrm{BI}_{it} + \beta_3\mathrm{CRDUM}_t + \beta_4\mathrm{CI}_{it}\cdot\mathrm{CRDUM}_t + \\ \beta_5\mathrm{BI}_{it}\cdot\mathrm{CRDUM}_t + \beta_6\mathrm{BANKCRISES}_{it} + \beta_7\mathrm{X}_{it} + \epsilon_{it} \quad (6)\end{aligned}$$

INNOV_{it} is the innovation measure for country i at time t proxied by logarithm of patents [in the baseline regression][16]. CI_{it} is a measure of external financing from capital markets, proxied by logarithm of market capitalization and BI_{it} is bank market indicator, proxied by the logarithm of bank credit extended to the private sector by domestic banks. CRDUM_t and $\mathrm{BANKCRISES}_{it}$ are dummy variables for liquidity crises years. CRDUM_t, the recent liquidity crisis dummy variable, takes the value of 1 for the crisis years of 2008 and 2009 for all countries. However, $\mathrm{BANKCRISES}_{it}$ is a country specific variable and takes the value of 1 in a particular credit crisis year for a specific country[17]. X is a vector of control variables that includes

[15] Additionally, given our GMM methodology, the use of a more parsimonious model mitigates the over-fitting problem by reducing the number of instruments used [see Roodman (2009)].

[16] Later, alternative measures of innovation in the robustness checks are also introduced.

[17] Incorporating both dummies into a single $\mathrm{BANKCRISES}_{it}$ dummy does not change the results in any way, see data description for information on categorization of bank crisis years.

demand for credit proxies, country specific individual effects and time dummies, while ϵ_{it}, is the idiosyncratic error term [see data description for more details].

The main variables of interest are the coefficients of capital and bank market indicators [β_1 and β_2]. After controlling the effect of crisis on innovation through the crisis dummy and relevant control variables, statistical significance of capital and bank market indicators i.e. positive β_1 and β_2 gives us the relevance of external access to finance as a factor positively influencing innovation. The recent liquidity crisis dummy and interaction terms with the main explanatory [credit supply] variables are also included in the list of regressors because of the severity of the recent liquidity crisis. The interaction terms of bank and capital market indicators with crisis dummy is included to assess whether the relationship between finance and innovation changed for the crisis years. On the other hand, the magnitude and statistical significance of the coefficients enables us to assess whether innovation is more dependent on market or bank based lending[18]. Likewise, the BANKCRISES dummy, representing general (country-specific) banking crises in our sample period, is also included to account for structural breaks and improve efficiency of the baseline equation [see data description for more details].

In order to model the impact of past knowledge base and credit availability on innovation [as it takes time for credit availability to translate into successful innovations] one needs to move away from standard static panel models. A dynamic panel data model that includes unrestricted lag length structures is considered. This also allows one to control for short run dynamics i.e. out of equilibrium innovation due to expectation formation, adjustment costs and business cycle effects. The equation of the following type in log-log form is estimated:

$$\text{A(L) INNOV}_{it} = \beta\ (L)\ \text{V}_{it} + \delta_i + \lambda_t + \epsilon_{it} \tag{7}$$

where V is a vector of all the explanatory variables mentioned above, β (L) is the associated polynomial in the lag operator for corresponding explanatory variables and A(L) denotes the lag polynomial for the dependent variable. However, one problem with estimating equation (7) directly is the inherent correlation of δ_i with lagged dependent variables which makes standard panel data models inconsistent [see Verbeek (2008)]. Anderson and Hsiao (1982) propose using lagged levels in the differenced equation and show that this gives us a consistent estimator. Arellano and Bond (1991), under

[18]This becomes possible, as both measures of bank and capital market financing are measured and normalized in the same units.

the assumption of no autocorrelation of the error terms[19], improve upon the efficiency of the first difference IV estimator by adding more information [moment conditions] and replacing IV by GMM estimation, where instrument matrix includes past level values of lagged dependent variable in the lagged differenced equations[20]. However, Blundell and Bond (1998) show through Monte Carlo experiments that the Arellano and Bond (1991) estimator suffers from downward bias in the case of near unit root processes and when the ratio of variance of fixed effects and error terms becomes large [a typical result when working with small T]. Moreover, they show that Arellano and Bover (1995) GMM system estimator, which adds moment conditions of level equation, where lagged differences are used as instruments in the level equation, not only displays better small sample properties but also mitigates the so-called weak instrument problem in GMM difference estimator i.e. weak correlation of past values in levels and variables in differences. Nevertheless, this requires additional assumptions on initial condition process. In the current framework, this assumption implies that countries cannot accurately predict future shocks and data is generated from a stationary process [Blundell and Bond (1998)]. Formally, the following assumption on the initial condition process needs to be satisfied:

$$E(\text{INNOV}_{i,1}\epsilon_{i,t}) = 0 \qquad \text{for } i = 1, \ldots, N \textit{ and } t = 2, \ldots, T \tag{8}$$

This is equivalent to assuming that future shocks to innovation are unknown to countries. Additionally, the use of the GMM system estimator also requires additional $T-3$ moment conditions to be satisfied i.e.

$$E(\Delta\text{INNOV}_{i,t-1}(\delta_i + \epsilon_{it})) = 0 \qquad \text{for } i = 1, \ldots, N \textit{ and } t = 4, 5, \ldots, T^{21} \tag{9}$$

Equation (4) implies that correlation between level values of right-hand side (RHS) variables and country specific fixed effects is allowed. However, correlation with differences of RHS variables and country-specific effects is disallowed. In the present context these moment conditions are fulfilled, for example, if the difference of logged innovation is uncorrelated with country specific effects, δ_i and shocks in the future periods, ϵ_{it}[22].

[19]Hence, the use of F-Statistics to select lag lengths on unrestricted lag length structures.

[20]It should be noted here that instruments are only valid if errors do not display autocorrelation.

[21]These moment conditions are naturally extended to other regressors.

[22]The similarity of magnitude of estimated coefficients across GMM Difference and System seem to imply that the violation of this assumption is not a major issue.

Particularly, dynamic panel difference and system GMM approaches are applied and compared. Difference in Sargan test is used to evaluate the validity of additional moment conditions in the system GMM as proposed by Blundell and Bond (1998). This is possible since GMM difference moment conditions are a strict subset of moment conditions in the GMM system estimator. In the present framework, differencing removes the time invariant country idiosyncrasies and various internal instruments in the moment conditions control for endogeneity of lagged dependent and independent variables. Endogeneity is a particular issue here because of the possibility of a feed back effect from GDP and innovation to the degree of financial access and because of common effects of omitted variables on both income levels and financial access. The current methodology circumvents this problem by using lagged differences in level equation and lagged level values in the differenced equation. It not only provides consistent estimates with lagged dependent variables but it also accommodates country specific heterogeneity, endogenous[23] explanatory variables and measurement errors [see Baltagi (2005)].

Nevertheless, as Bond (2002) emphasizes, autocorrelation in errors biases the results of both GMM difference and system estimators. Ergo a test for autocorrelation as proposed by Arellano and Bond (1991) is performed. Additionally, Bond (2002) recommends investigating the time series properties of individual series when using GMM estimators. Identification requires that the series are not unit root processes. Windmeijer et al. (2002) compare different unit root tests for panel data and conclude that the simple t-tests based on OLS estimates provide higher power than more technical tests [as OLS estimator is biased upwards].

It is noted that the large number of instruments used in GMM estimators might force statistical significance for endogenous explanatory variables. Roodman (2009) studies this "over-fitting" of the GMM system estimator more explicitly and his advice regarding performing the difference in Sargan test and testing the sensitivity to different number of instruments is explicitly taken into account during the course of estimations and robustness checks. Moreover, Bun and Kiviet (2006) show that the bias in the GMM estimators increases with the number of instruments. Hence, instruments in "compact form" are used. One year lags for predetermined variables [unemployment and GDP] and two year lags for endogenous variables [MarCap and CreditBanks] are used, based on over-identification tests[24]. Failure to reject the

[23]On the other hand, standard two stage least squares [2SLS] consider all the non-instrumented variables exogenous, hence one endogenous regressor can bias all the coefficients estimates.

[24]Lagged levels as instruments for differenced moment equations and lagged differenced variables for level equations are used.

validity of instruments when treating demand variables as predetermined dictated this choice. However, treating the demand variables as endogenous do not change the results in any significant way [see Table 8, column 19].

Given the lags of individual series and full model as determined by joint significance of test statistics, the following baseline equation is estimated[25]:

$$
\begin{aligned}
\text{INNOV}_{it} &= \beta_0 + \alpha_1\text{INNOV}_{it-1} + \alpha_2\text{INNOV}_{it-2} + \alpha_3\text{INNOV}_{it-3} + \beta_4 GDP_{it} + \beta_5 GDP_{it-1} \\
&+ \beta_6 UNEMPLOYMENT_{it} + \beta_7 UNEMPLOYMENT_{it-1} + \beta_8 MARCAP_{it} \\
&+ \beta_9 MARCAP_{it-1} + \beta_{10} MARCAP_{it-2} + \beta_{11} BANKCREDIT_{it} + \beta_{12} BANKCREDIT_{it-1} \\
&+ \beta_{13} BANKCREDIT_{it-2} + \beta_{14} BANKCREDIT_{it}{\cdot}\text{CRDUM}_t + \beta_{15} MARCAP_{it}{\cdot}CRDUM_t \\
&+ \beta_{16} CRDUM_t + \beta_{17} BANKCRISES_{it} + \delta_i + \lambda_t + \epsilon_{it} \qquad (10)
\end{aligned}
$$

The GMM estimators used here utilizes more than one instrument to estimate an individual parameter. Therefore, the model is overidentified. To evaluate the validity of the instruments Sargan tests for the joint validity of instruments are performed for both GMM difference and system estimators. This is particularly useful, as Arellano and Bond (1991) note that this test has the tendency to over-reject the null of valid instruments, for instance, when the model is misspecified. Hence, non-rejection of Sargan test not only serves as a test for validity of instruments but also as a general specification test.

4.2 Preferred Approach

First, a simple AR (p) process of variables[26] using different estimators are presented in Table 3. Column 1 presents the OLS estimates which are upward biased in dynamic panels. Column 2 and 3 gives the results of estimations from fixed effects and GMM-Difference estimators, respectively, both of which are biased downwards in persistent dynamic panels, while column 4 shows estimates using the GMM system estimator that provides consistent estimates for dynamic panels and persistent series. The estimations in Table 3 also serve to test for the presence of unit roots and explain the usefulness of different estimators in the present context. Additionally, Sims (2010), in a critique of single equation models has stressed the need to report and interpret parameter estimates from multiple estimators so the true uncertainty of

[25] All variables, except the dummies are in their natural logarithms. Possible non-linear relationships are later evaluated in the robustness section.

[26] Similar results are found for other series but only the dependent variable, one credit and demand variable is shown.

results can be brought to light. Lags are selected based on joint significance of the variables. This is statistically useful in identifying dynamic panel models where the assumption of no autocorrelation is needed for GMM difference and system estimators. From an economic perspective introducing lags of innovation in the main estimations imply that innovation in the past has an independent impact on current innovation. This is also a common finding in innovation research, where it is asserted that innovations in the past increases the base of knowledge for further innovations [see Reenen (1997); Piva and Vivarelli (2005)].

The results of Table 3 suggest that although the series are persistent but they do not contain unit roots. It can be seen that even OLS estimates which are theoretically biased upwards, are not exact unit root processes [see Windmeijer et al. (2002)]. Alternative, traditional Fisher type unit root tests for panel data [see, Choi (2001)] also reject the null of unit roots at conventional significance levels[27].

In line with the direction of biases, the estimated coefficients behave exactly as expected providing first support for the unbiasedness of the estimates and our estimation of equation in levels. In dynamic models not only is OLS biased upwards but fixed effects are biased downwards [Baltagi (2005)]. A consistent estimator lies between these upper and lower bounds. Hence, from Table 3 we can also conclude based on this boundedness that the GMM system estimator [column 4] is most reliable with the data at hand.

Staiger and Stock (1997) highlight the so-called weak instrument problem for simple instrumental variable regressions and show how persistent series display large finite sample [downward] bias. Blundell et al. (2000) augment this research and document how the GMM difference estimator displays the same weak instrument problem as its IV counterpart when the series are persistent. This occurs because lagged levels provide weak instruments for the differenced equations when the true value of lagged dependent variables approaches unity or ratio of variance of fixed effects and error term becomes large.

Apart from the statistical advantage, intuitively, the GMM system estimator exploits greater available information from the data, i.e. it uses information from the moment equations both in levels and differences. More importantly, the GMM system estimator is preferred as it explicitly takes into account the variation in the level relationship i.e. the changes in the level of access to finance and innovation which is exactly relationship we

[27]The presence of unit root is rejected at conventional significance levels but this is not emphasized upon as these methods test the very weak null that all panels contain unit roots.

Table 3 AR(p) process of variables

	(1)	(2)	(3)	(4)
VARIABLES	(OLS) PATENTS	(FE) PATENTS	(GMM-DIFF) PATENTS	(GMM-SYS) PATENTS
L. PATENTS	0.765***	0.682***	0.644***	0.709***
	0.100	0.102	0.021	0.0147
L2. PATENTS	0.0947	0.0856	0.0865***	0.105***
	0.0729	0.0686	0.0226	0.0188
L3. PATENTS	0.133***	0.110*	0.0981***	0.0922***
	0.0489	0.0579	0.0185	0.0177
Constant	0.0817***	0.879***	1.219***	0.682***
	0.0265	0.273	0.119	0.0716
Observations	2463	2463	2345	2463
Number of Countries	84	84	84	84
VARIABLES	MAR_CAP	MAR_CAP	MAR_CAP	MAR_CAP
L. MAR_CAP	0.821***	0.688***	0.637***	0.609***
	0.0393	0.0392	0.0329	0.0238
L2. MAR_CAP	0.0620*	0.0194	0.00682	0.0163
	0.0336	0.0311	0.0246	0.0164
Constant	0.486***	1.090***	1.358***	1.374***
	0.0764	0.0769	0.096	0.0713
Observations	1395	1395	1315	1395
Number of Countries	78	78	78	78
VARIABLES	GDP	GDP	GDP	GDP
L. GDP	0.995***	0.983***	0.980***	0.997***
	0.0011	0.0055	0.0016	0.0013
Constant	0.0273**	0.165***	0.189***	0.0456***
	0.0108	0.0462	0.0135	0.0109
Observations	3501	3501	3417	3501
Number of Countries	84	84	84	84

Standard errors below coefficient estimates
*** p<0.01, ** p<0.05, * p<0.1

want to study.

5 Results

5.1 Main Results

The main results are presented in Table 4, where equation (10) is estimated using the four estimators shown in Table 3. Again, a similar pattern is observed with OLS giving overestimated and fixed effects giving underestimated coefficients for lagged dependent variables [column 5 and 6, respectively][28]. This confirms the direction of bias in the estimated coefficients and suggests that equation (10) when estimated by the preferred GMM system estimator is correctly specified.

The interpretation of GMM difference and system estimator [column 7 and 8, respectively] is rather simple. One can simply obtain a log-log percentage interpretation of the level equation[29] [see Bond (2002) for more details]. The estimations show that access to external financing has a significant and rapidly propagating positive effect on innovation. According to the preferred GMM system estimator [Table 4, column 8], on the aggregate level better access to capital and bank market lending positively influences innovation. The effect of access to finance is felt rather quickly, with positive effects felt only after a one year lag from both bank and capital market lending.

However, one should note that the lag of market capitalization only gains individual significance at conventional levels in the GMM system estimator [Table 4, column 8]. I argue that this is because GMM-SYS not only incorporates information in first differenced moment equations as in GMM-Diff estimator, but also information in level equations, hence is the most efficient estimator in a class of GMM estimators with large N and small T [Baltagi (2005)]. Also, the GMM system is preferred, because under the current context i.e. presence of lagged dependent variables as regressors [FE and OLS biased] and persistence of series [GMM-Diff biased] it gives us consistent estimates. Similar reasoning applies to Bank Credit and other regressors, hence our penchant for GMM-SYS estimator while interpreting coefficients. Never-

[28]For example, estimates of lagged dependent variable add up to be 0.981 and 0.821 for OLS and Fixed Effects, respectively. Moreover, the GMM difference and System estimators lies between these lower and upper bounds. As shown in table 3 the series are highly persistent and therefore the lagged dependent variable in the GMM difference estimator is expected to be downward biased. This again is checked out with the lagged dependent variable summing up to 0.787 for GMM difference and 0.959 for GMM system estimator.

[29]As variables are in natural logarithms.

Table 4 Results

	(5)	(6)	(7)	(8)
VARIABLES	(OLS) PATENTS	(FE) PATENTS	(GMM-DIFF) PATENTS	(GMM-SYS) PATENTS
L. PATENTS	0.851***	0.704***	0.685***	0.807***
	0.0303	0.0318	0.0317	0.023
L2. PATENTS	0.0435	0.0456	0.0426	0.0492
	0.0388	0.0381	0.0376	0.0328
L3. PATENTS	0.0973***	0.0769**	0.0608**	0.111***
	0.0286	0.0301	0.0301	0.029
GDP	0.425	0.547*	0.584*	0.26
	0.265	0.311	0.311	0.282
L. GDP	-0.452*	0.125	0.112	0.294
	0.264	0.302	0.302	0.279
UNEMPLOYMENT	0.0865*	0.138***	0.154***	0.0658
	0.0495	0.0518	0.0513	0.0502
L.UNEMPLOYMENT	-0.126***	0.0363	0.0379	0.0566
	0.0483	0.0508	0.0498	0.0497
MAR_CAP	0.0134	0.0214	0.018	-0.0297*
	0.017	0.0188	0.0187	0.0177
L. MAR_CAP	0.0239	0.0188	0.0306	0.0411**
	0.0204	0.0204	0.02	0.019
L2. MAR_CAP	0.00401	0.0187	-0.0261*	0.0207
	0.0156	0.0156	0.0154	0.0146
CREDITBANKS	0.0248	0.0198	0.0489	0.0292
	0.0552	0.0615	0.063	0.0608
L. CREDITBANKS	0.174**	0.161**	0.178**	0.163**
	0.0786	0.0764	0.077	0.0764
L2. CREDITBANKS	-0.110**	0.0888	0.0708	-0.0994*
	0.0548	0.0572	0.0566	0.057
CRDUMxCreditBanks	0.112	0.0629	0.0981	0.0554
	0.168	0.187	0.175	0.153
CRDUMxMAR_CAP	0.109	0.0463	0.0419	0.0698
	0.0985	0.0976	0.095	0.0966
CRDUM	0.0195	0.00417	0.00309	0.00751
	0.0358	0.0375	0.0372	0.0332
BANKCRISES	0.0002	0.00014	2.4E-05	0.00028
	0.00028	0.00028	0.00028	0.00029
Constant	0.203**	-2.803***	-3.156***	0.128
	0.0894	0.85	0.914	0.152
Time Dummies	YES	YES	YES	YES
Observations	1045	1045	950	1045
Number of Countries	76	76	76	76
Sargan	-	-	0.128	0.2305
Diff in Sargan	-	-	-	0.99
Autocorrelation (m2)	-	-	0.747	0.831

Standard errors below coefficient estimates
*** p<0.01, ** p<0.05, * p<0.1
P-values for Sargan, Diff-in-Sargan and Autocorrelation tests are also reported.

theless, it should be noted that though market capitalization is individually insignificant, the coefficients of both bank credit and market capitalization are jointly significant at conventional significance levels across all estimators. For example in GMM difference estimator, where market capitalization is individually insignificant, the p-values of joint significance of bank credit and market capitalization decreases to 0.033. Consequently, multicollinearity might also be driving the relatively high standard errors and failure of the less efficient estimators to gain conventional significance levels for market capitalization[30].

Comparisons on the magnitudes of bank and capital market lending can be easily made, as they are both in their natural logarithms, normalized by GDP and measured in US dollars. The coefficient estimates suggest that the economic significance of the bank lending channel is much larger relative to capital market lending. The magnitude is larger for bank credit across all estimators [see Table 4, column 5 through 8]. More specifically, according to our preferred GMM-SYS, a 10% increase in bank lending increases innovation by around 1.63% but a similar increase in capital market lending only increases innovation by 0.41%. To exploit the maximum variation in data and understand the level relationship between finance and innovation the equation in levels is preferred. However, the results are essentially unchanged when regression are run in terms of annual growth rates[31]. This is in line with Arestis et al. (2001) findings, where they document that bank markets have a higher growth enhancing effect relative to capital markets. Hence, the results here provide suggestive evidence that higher innovation output from bank financing might be driving their result. Moreover, the economically and statistically larger bank credit coefficient across all estimators also points towards a stronger relationship between bank credit and innovation. The robust bank innovation relationship and relatively weak capital markets innovation relationship might be driven by what Stiglitz (1985) called the free-rider problem due to excessive transparency in well developed capital markets where immediate revelation of information discourages investors from researching firms that reduces identification of innovative projects. Moreover, Manso (2011) notes that this excessive transparency may also put pressure on the managers to meet short-term earning expectations reducing the incentives for innovation, particularly for long term and exploratory innovations. Banks are thought to mitigate these disincentives by privatizing information ac-

[30]Correlation coefficient between bank credit and market capitalization is 0.62, statistically significant at 1% significance level.

[31]With growth rates, a 10% increase in innovation raises bank lending by 1.62% and capital market lending by 0.37% (when estimated by non-dynamic model with fixed effects).

quisition and establishing long-run relationships with firms [Gerschenkron (1962); Bhide (1993) and Rajan and Zingales (1998b)].

As we have more instruments than the estimated parameters, the model is over-identified. Hence, Table 4 also reports the p-values of the Sargan test. The test fails to reject the null of valid moment conditions at any conventional significance levels for both GMM-DIFF and GMM-SYS. As noted earlier GMM system estimator augments additional moment conditions [equation in levels], these additional moment conditions are explicitly tested through differences in Sargan test, where validity of the level moment conditions are not rejected with a p-value of 0.99. Moreover, the Arellano and Bond (1991) test for autocorrelation fails to reject the null of no autocorrelation. This test is important as it explicitly tests the crucial assumption for GMM estimators i.e. whether the errors in level equations are not autocorrelated[32].

One should also note that the second year lag of bank credit and contemporaneous effect of market capitalization enters with a negative sign which is statistically significant. This is a common result in dynamic equations and represents short-run dynamics i.e. an adjustment towards long-run equilibrium value [Bond (2002)]. Moreover, accounting for the severe negative shocks to innovation in 1994 and 2000 [see Figure 1] in the form of time specific dummies takes away the statistical significance of the second year lag for credit by banks and contemporaneous effect of market capitalization, while maintaining the economic and statistical significance of first year lags of Bank Credit and Market capitalization [see column 9, Table 5].

Furthermore, one should also note in column 11 of Table 5 that the interaction term of the recent financial crisis and market capitalization becomes significant when demand controls are left out. The negative coefficient implies that in the crisis years of 2008 and 2009, the relationship between access to finance and innovation changed. However, this effect seems to stem from the severe demand shock in the crisis years, which is removed once demand controls are put in place. This in turn implies that there was indeed a demand for credit effect present which was controlled for in the baseline regression.

Nevertheless, as was seen in Figure 1, there was drastic simultaneous reduction in GDP, market capitalization and patents post crisis. As around 15% of our samples' time dimension falls in this period, it is very possible that the positive structural relationship is only driven by the simultaneous drops in the crisis years. Hence, we limit our sample period from 1988 to 2007 to estimate equation (10). Column 12 of table 5 gives the results. Again we observe strikingly similar results with innovation being positively

[32]Following, Arellano and Bond (1991), second order autocorrelation [m2] in the differenced equation gives us the autocorrelation in the level equation.

Table 5 Discussion of Results

	(9)	(10)	(11)	(12)
VARIABLES	(GMM-SYS) PATENTS	(GMM-DIFF) PATENTS	(GMM-SYS) PATENTS	(GMM-SYS) PATENTS
L. PATENTS	0.805***	0.658***	0.760***	0.778***
	0.0228	0.0295	0.0525	0.0254
L2. PATENTS	0.0366	0.0732**	0.0567	0.0624*
	0.0323	0.0345	0.0707	0.0352
L3. PATENTS	0.127***	0.127***	0.147***	0.137***
	0.0284	0.0278	0.0507	0.0312
MAR_CAP	0.0233	0.0122	0.0181	-0.0302*
	0.0165	0.0186	0.0178	0.0183
L. MAR_CAP	0.0447**	0.0217*	0.0281*	0.0390*
	0.0186	0.0184	0.0145	0.0211
L2. MAR_CAP	0.0195	0.0176	0.0263	0.0136
	0.0141	0.0151	0.0179	0.0146
CREDITBANKS	0.00949	0.0364	0.0114	0.00983
	0.0598	0.0612	0.0527	0.0639
L. CREDITBANKS	0.150**	0.159**	0.142**	0.139*
	0.0751	0.0766	0.0807	0.0791
L2. CREDITBANKS	0.0854	0.0657	-0.112*	0.0756
	0.0562	0.0565	0.062	0.0608
CRDUMxCreditBanks	0.0144	0.0226	0.0066	
	0.0329	0.0364	0.0417	
CRDUMxMAR_CAP	0.0003	0.00019	-0.000401*	
	0.00029	0.00029	0.00023	
CRDUM	0.0214	0.179	0.0684	
	0.146	0.164	0.191	
BANKCRISES	0.0942	0.0704	0.057	0.0498
	0.0963	0.102	0.0651	0.0953
GDP	0.272			0.680**
	0.27			0.307
L. GDP	0.306			-0.705**
	0.267			0.302
UNEMPLOYMENT	0.0537			0.065
	0.0484			0.0537
L.UNEMPLOYMENT	0.0513			0.0717
	0.0484			0.052
Constant	0.231*	0.840***	0.0662	0.129
	0.139	0.244	0.151	0.154
Observations	1045	950	1045	820
Number of Countries	76	76	76	76

Standard errors below coefficient estimates
*** p<0.01, ** p<0.05, * p<0.1

related to market capitalization and bank credit, with the latter having larger magnitude[33].

The [joint] insignificance of further lags of credit variables and reduction in significance of lagged patents when credit variables are left out also seem to suggest that reduced access to finance has a long-run adverse effect on innovation as firms are reducing the number of applications they file as opposed to delaying the filing of applications. The dynamic nature and log-log form of the model enables one to explicitly compute short-run and long-run elasticities.

Table 6 presents SR (short-run, β) and LR (long-run, κ) elasticities of financial variables when equation (10) is estimated by the preferred GMM-SYS. The short run coefficient for the first year lags are shown in column 13[34]. We see again that 10% increase in market capitalization and bank credit increases patents by 0.41% and 1.63%, respectively, after a one year lag. As emphasized in the model, this effect is interpreted as a reduction in delay of filing of patents for pipeline projects. However, in the long-run [column 14], the elasticity dramatically increases for bank credit, where the same 10% increase of bank credit increases patent applications by about 21.2%. This is interpreted as the real impact of better financial access producing more patent applications[35].

It should also be noted that though the recent crises was accompanied with unprecedented reduction in liquidity [as seen in Table 1/Figure 1], this did not change the positive structural relationship between innovation and external access to finance. Hence, the interaction term of crisis dummy and access to finance is insignificant for all specifications with demand controls.

5.2 Post-Crisis Analysis

As shown in Table 1/Figure 1, there was a simultaneous drop observed in innovation, credit supply and demand variables post-crisis. Additionally, as documented earlier this particular crisis was a credit supply shock. Hence, it is informative to check the robustness the current findings by exploiting the variation in innovation, pre and post crisis years. This also permits us to

[33]The statistically significant negative signs of credit supply variables can again be removed through omitting either 1994 and/or 2000 outliers.

[34]Only first year lags are presented as only they are statistically significant; here the regression is run without the year 2000 outlier.

[35]The dramatic increase from short to long-run elasticities for the bank financing channel is driven by the persistence of innovation series. Nevertheless, the market financing channel barely budges for the long-run because of the negative, though statistically insignificant, contemporaneous coefficient for market capitalization which are taken into account based on Woodridge (2009) recommendation.

Table 6 Short-Run and Long-Run Elasticities of credit supply variables

VARIABLES	(13) SR β	(14) LR κ
MAR_CAP	0.041**	0.040*
	(0.032)	(0.075)
CREDITBANKS	0.163**	2.12***
	(0.050)	(0.0005)

p-values in the parenthesis
*** p<0.01, ** p<0.05, * p<0.1

empirically decompose the channels through which this shock is propagated. Hence, to quantify how much of a drop in innovation was due to a reduction in supply of credit in the recent liquidity crisis, variance decompositions based on our preferred GMM system equation are presented. This is done by limiting the sample to the post-crisis period of 2008 to 2010 and estimating equation (10) by the GMM-SYS[36]. As expected there is a loss of precision due to fewer observations. However, the drastic reduction of time periods should not be too much of an alarm as GMM-SYS is specifically designed to accommodate small time periods. Woodridge (2009) recommends focusing on the cumulative effects by adding the distributive lags to get the long-run effects when sample sizes are small. Table 7 gives the results of the collapsed regression with the cumulative effects along with the corresponding variance decompositions[37].

We see around 13% of reduction in innovation in the crisis years can be explained by a reduction in GDP. Moreover, a 4% drop that is highly statistically significant is explained through reduction in capital market lending. Similarly, around 15% of reduction in innovation can be attributed to reduction in bank lending. This is exactly in line with the previous full sample finding, where innovation is more dependent on bank financing. Although, the magnitude of bank lending coefficient is strikingly close to our full sample estimate, the loss of precision has made it [jointly] statistically insignificant at conventional significance levels. Lastly, it should also be noted that the

[36]Insignificant dummy variables and interaction terms are dropped to focus on the credit demand and supply channel.

[37]See Appendix B for more details on variance decomposition.

Table 7 Variance Decomposition Post Crisis

	Cumulative Estimates	Variance Decomposition
	(15)	(16)
VARIABLES	PATENTS	
GDP	0.1162***	13.25%
	0.0038	
MAR_CAP	0.0671***	4.83%
	0.0001	
CREDITBANKS	0.1686	15.55%
	0.3029	
Unemployment	0.0570	1.65%
	0.2950	
Past Patents	0.92***	64.67%
	0.0000	
Observations	228	
Number of Countries	76	

p-values of joint significance below the coefficient estimates
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

majority of the variance in innovation can be explained by past innovations, while variance in innovation due to unemployment is neither economically nor statistically significant.

6 Robustness

To evaluate the sensitivity and robustness of the results, two approaches are undertaken. First, econometric robustness checks for the GMM estimator, as advised by Roodman (2009), are performed. Secondly, economic robustness is shown where alternate and normalized measures of innovation are introduced, showing exceedingly similar results. Moreover, interaction terms of financial access variables and GDP per capita are included in the baseline regression to gauge whether the results differ for rich and poor countries. As discussed earlier, secondary influences of FDI, tertiary enrolment and exports on innovation are also put in the baseline equation to judge the validity of the results.

Roodman (2009) carefully analyses the GMM difference and system estimators. He notes although these estimators are powerful tools to account for endogeneity, it might also "overfit" endogenous variables and weaken the Sargan test of instruments' joint validity. Consequently, in the base line regressions full set of available instruments are not used to avoid this overfitting problem. Moreover, Roodman (2009) recommends that in order to gain from the advantage of using GMM estimators in dynamic panels and not suffer from the disadvantages, Sargan tests of joint validity on subset of instruments should also be performed to investigate if a change in instruments overturns the results and/or rejects the test. Table 8 varies the number of instruments and reports the estimated coefficients with the Sargan test results. Column 17 of this table gives the base line regression as in column 8 of Table 4. As noted earlier, the credit variables are considered endogenous and demand variables as predetermined[38]. Column 18 considers all variables as predetermined, while column 19 considers all variables as endogenous. Lastly, column 20 uses full set of available instruments. It can be seen that varying the number of instruments across columns does not change the positive relationship between innovation and access to finance. One can also see that the magnitude of first year lags of bank credit and market capitalization remain extremely similar i.e. close to the baseline 0.16 and 0.04 range, respectively. Moreover, it is seen in Table 8 that at no specification does the Sargan test reject the joint validity of instruments.

[38]Dependent variable is also considered endogenous, two and one year lags for endogenous and predetermined variables, respectively, as is standard are used.

Table 8 Robustness with different instruments

	(17)	(18)	(19)	(20)
VARIABLES	PATENTS	PATENTS	PATENTS	PATENTS
GDP	0.26	0.24	0.268	0.26
	0.282	0.284	0.28	0.28
L. GDP	0.294	0.275	0.31	0.299
	0.279	0.281	0.278	0.277
UNEMPLOYMENT	0.0658	0.0638	0.0808	0.0850*
	0.0502	0.0504	0.0502	0.05
L.UNEMPLOYMENT	0.0566	0.0574	-0.0836*	-0.0852*
	0.0497	0.0499	0.0484	0.0481
MAR_CAP	-0.0297*	-0.0328*	0.0255	0.0252
	0.0177	0.0178	0.0172	0.0172
L. MAR_CAP	0.0411**	0.0428**	0.0404**	0.0414**
	0.019	0.0191	0.0186	0.0186
L2. MAR_CAP	0.0207	0.0205	0.0133	0.0122
	0.0146	0.0148	0.0142	0.0142
CREDITBANKS	0.0292	0.0401	0.0135	0.0208
	0.0608	0.0616	0.0607	0.0605
L. CREDITBANKS	0.163**	0.154**	0.168**	0.170**
	0.0764	0.077	0.0775	0.0776
L2. CREDITBANKS	-0.0994*	-0.0981*	0.0778	0.0818
	0.057	0.0575	0.0546	0.0546
CRDUMxCreditBanks	0.00751	0.00768	0.00335	0.00147
	0.0332	0.0333	0.0335	0.0335
CRDUMxMAR_CAP	0.00028	0.00025	0.00021	0.00019
	0.00029	0.00029	0.00028	0.00028
CRDUM	0.0554	0.0506	0.0529	0.0726
	0.153	0.153	0.154	0.154
BANKCRISES	0.0698	0.0672	0.0524	0.0558
	0.0966	0.097	0.0944	0.094
Constant	0.128	0.137	0.247*	0.246*
	0.152	0.153	0.149	0.149
Assumptions	Baseline	Predetermined	Endogenous	All Instrum
Sargan p-value	0.231	0.165	0.415	0.496

Standard errors below coefficient estimates

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The highly significant lagged patents are not displayed in the table.

Next, alternate measures of innovation: R&D expenditures, number of researchers and employment in high tech sectors, albeit, with limited sample are used as dependent variables to estimate equation (10) by GMM-SYS[39]. However, due to the small number of observations insignificant third year innovation lags, dummies and interaction terms are dropped to gain efficiency. Table 9 shows the results of these regressions, where as before due to the limited sample cumulative sum of lags are used to gauge the long-run effects.

Column 21 of Table 9 uses R&D expenditures as a proportion of GDP as the dependent variable. Data for this regression is available for 66 countries. Moreover, the sample time period drops by 10 years. Nevertheless, after patents, this innovation measure has the largest degrees of freedom and is the most reliable. We see again that market capitalization and bank credit is significant and positively related to innovation. Interestingly, just like patents, the positive effect is only felt after a one year lag.

Furthermore, in line with our previous finding, the bank credit coefficient is [around 67 %] larger than market capitalization, again highlighting the importance of bank financing for innovation. Moreover, the demand variable is significant and positively related to innovation. Column 22 now replaces, R&D expenditures by [logarithm of] number of researchers. The sample size declines further and a loss of precision for every variable is observed. Although, statistically insignificant, we see that the magnitude of bank credit is [50 %] larger than market capitalization. Lastly, column 23 use total employment in knowledge intensive activities as dependent variable but now both the number of countries and time dimension decrease drastically. This innovation measure categorized noisy but important by Porter et al. (2002) gives results in line with our baseline regressions where credit variables and GDP is positively and statistically significantly influencing innovation with the magnitude greater for bank relative to capital market lending measure. Moreover, it should also be noted that Arellano and Bond (1991) test for autocorrelation fails to reject the null of no autocorrelation in all the regressions. Hence, the identifying assumption of no autocorrelation seems to be satisfied.

As discussed in the data description section, the growth without scale effects literature motivated the non-normalization of baseline innovation measure. To show that the results are not driven by scale effects, [logarithm of] patent applications as a portion of GDP is used to estimate equation (10) by GMM-SYS. The results are presented in Table 10, column 24[40]. It is seen

[39]Earlier normalization approach apply, see Table 11.

[40]It should be noted that the highly statistically significant lagged dependent variables and insignificant contemporaneous FDI, exports, enrolment, crisis dummies and their interaction terms are not shown in Table 11 to conserve space and focus on the main findings.

Table 9 Robustness with different Innovation Measures

VARIABLES	(21) R&D Exp	(22) Researchers	(23) EmployKIA
MAR_CAP	0.0371*** 0.0004	0.0224 0.298	0.0017*** 0.002
CREDITBANKS	0.050* 0.094	0.0336 0.333	0.024** 0.0292
L.R&D Exp	0.891*** 0.000		
L.Researchers		0.963*** 0.000	
L.EmployKIA			0.971*** 0.000
Constant	-0.374*** 0.11	0.0218 0.107	-0.249*** 0.0718
Time Dummies	YES	YES	YES
Demand Controls	YES	YES	YES
Observations	613	482	71
Number of Countries	66	57	10
Autocorrelation (m2)	0.2482	0.3543	0.2135

p-values of joint significance below coefficient estimates
*** p<0.01, ** p<0.05, * p<0.1
Note: The highly significant lagged innovation measures are not shown.

that the estimates are extremely similar to the baseline equation where the coefficient of bank credit is much larger than market capitalization. Interestingly, the one year lagged market capitalization under much of our scrutiny has the same coefficient estimate and standard error [till 4 decimal points] as in the non-normalized baseline equation. Additionally, the two year lag of bank credit and contemporaneous market capitalization is no longer [negatively] statistically significant even with the outlier year(s).

To access whether the access to finance and innovation link is more pronounced in rich vis-a-vis poor countries, access to finance variables are interacted with GDP. Column 25 in Table 10 gives the results. As before it is seen that the first year lags of credit and market capitalization are positive and statistically significant. Although, the interaction term of GDP with market capitalization is statistically insignificant but the interaction term with bank credit is statistically significant and enters with a negative sign. This is interpreted as access to bank credit being more important for innovation in poorer countries, which makes sense as most firms in developing countries are more reliant on bank relative to market financing.

Next, column 26 to 28 add FDI, exports and tertiary enrolment, respectively to the baseline equation. As outlined earlier, it is seen once GDP is included in the equation these measures lose their statistical significance. Moreover, it is seen that the positive relationship between access to finance and innovation persists. An unrestricted model with simultaneous inclusion of FDI, exports, enrolment and interaction terms of financial access variables with GDP and crisis dummy is estimated in column 29. The results are interesting though the identifying assumption of no autocorrelation is rejected at convention significance levels, hence relegating the discussion of these results only in the robustness section. Here the contemporaneous effect of bank lending and one year lag of market capitalization is statistically significant and positive, where as before the former is larger than the later. However, interestingly now both the interaction terms of financial variables with income levels are significant though they enter with opposite signs for bank and capital markets. For example, as before the bank credit enters with a negative sign which is interpreted as the effect of bank lending more pronounced for developing countries. Nevertheless, interaction term with market capitalization enters with a statistically significant positive sign, suggesting that capital markets impact innovation more in developed countries. This makes sense as well developed capital markets are an hallmark of advanced capitalistic economies. Also, one year lag of GDP and unemployment are positive and negative, respectively as before (not shown). However, now GDP is highly significant even in the GMM-SYS. Though exports and enrolment is insignificant, FDI enters with a significant negative sign. While

Table 10 Further Robustness Checks

	(24)	(25)	(26)	(27)	(28)	(29)
VARIABLES	PATENTSGDP	PATENTS	PATENTS	PATENTS	PATENTS	PATENTS
MAR_CAP	0.0249	0.0145	0.0246	0.0247	0.0269	-0.217**
	0.0175	0.0853	0.0173	0.0176	0.0179	0.0991
L. MAR_CAP	0.0411**	0.0447**	0.0352*	0.0444**	0.0421**	0.0345*
	0.019	0.019	0.0185	0.0188	0.0187	0.0193
L2. MAR_CAP	0.0182	-0.0275*	0.00942	0.0208	0.00273	0.00303
	0.0148	0.0149	0.014	0.0146	0.0141	0.0146
CREDITBANKS	0.0183	0.331*	0.038	0.0304	0.0145	0.595***
	0.0614	0.187	0.0585	0.0604	0.0643	0.201
L. CREDITBANKS	0.171**	0.173**	0.103	0.167**	0.137*	0.111
	0.0785	0.0774	0.0751	0.0769	0.0799	0.0856
L2. CREDITBANKS	0.0654	-0.0939*	0.056	-0.121**	0.0187	0.012
	0.0563	0.0568	0.0558	0.0562	0.0577	0.059
GDPxBI		-0.0374*				-0.0749***
		0.0203				0.0224
GDPxCI		0.00161				0.0264**
		0.00995				0.0117
L. FDI			0.00882			-0.0245*
			0.0112			0.013
L2. FDI			0.0164			-0.0248*
			0.0119			0.0136
L. Exports				0.00711		0.0219
				0.116		0.129
L2. Exports				0.0509		0.0827
				0.122		0.0944
L. Tertiary Enrol					0.0345	0.118
					0.22	0.225
L2. Tertiary Enrol					0.127	0.021
					0.212	0.147
Constant	0.212	-1.308*	0.143	0.0703	0.0653	-1.684**
	0.185	0.671	0.147	0.192	0.182	0.723
Time Dummies	YES	YES	YES	YES	YES	YES
Demand Controls	YES	YES	YES	YES	YES	YES
Observations	1045	1045	937	1045	726	687
Number of Countries	76	76	70	71	68	68
Autocorrelation (m2)	0.7848	0.7779	0.2618	0.6851	0.0705	0.0389

p-values of joint significance below coefficient estimates
*** p<0.01, ** p<0.05, * p<0.1
Note: GMM-System estimator is applied across all columns, while insignificant regressors and [highly] significant lagged dependent variables are not shown to conserve spaces and emphasize the results.

much has been said on the relationship between FDI and GDP [see, for example Hansen and Rand (2006); Borensztein et al. (1998); Li and Liu (2005) and Javorcik (2004)], I am reluctant to draw any conclusions as the autocorrelation in estimated equations of column 28 and 29 [Table 11] biases the coefficient estimates and makes the results suspect.

The recent proposition set forth by Cecchetti and Kharroubi (2012) and Arcand et al. (2012) is also assessed. They argue that the effect of financial sector on real activity is non-monotone and is characterized by an inverted-U shaped relationship. This diminishing returns to access to finance is checked by adding quadratic terms for both bank and capital market indicators. This is only checked out for capital market indicator in the pooled OLS regression without country fixed effects and lagged variables (not shown). On the other hand, the within transformation gives us statistically significant positive quadratic term, implying increasing returns to innovation from financial access. Moreover, the multiplier effect of finance on innovation in the long run with a 10% increase in bank financing inducing a 21.2% in innovation in the long run makes the increasing returns interpretation particularly tempting. Nevertheless, including dynamics with the within transformation makes the quadratic term insignificant across all estimators. Hence, the linear estimates are preferred. Lastly, as GDP and unemployment might not capture expectations about future demand, S&P price index was added in the baseline equation in an attempt to account for expectation formation. Although the main results remain the same but the price index is statistically insignificant. [Lachenmaier and Rottmann (2011)] emphasize that the ability of panel GMM estimators by capturing 'short-run dynamics' and constructing internally generated instruments allows it to account for this expectation formation effect and other omitted variable bias. Hence, the statistical insignificance of the price index is unsurprising. However, a better proxy or alternate methodology that explicitly accounts for future expectation will help in assessing the conclusion reached here.

7 Conclusion

The article studied innovation as one of the channels through which better access to finance influences long run growth. Dynamic panel GMM models, which accommodates country specific heterogeneity, endogenous explanatory variables and measurement errors were used to analyse this channel. Evidence from a broad panel of 76 countries from year 1988 to 2010 points towards the relevance of better access to finance in facilitating innovation across countries. This result is robust to a host of alternate specifications.

It is also seen that different measures of innovation, varying number of instruments and assumptions on exogeniety of variables, fails to overturn the positive structural relationship between better access to finance and innovation. The magnitude of estimations suggest that this positive relationship mainly stems from bank as opposed to capital market lending with the effect from bank financing more pronounced in lower income countries. Furthermore, in line with the full sample finding, the analysis of recent liquidity crisis showed that the large drop in liquidity had a direct negative effect on innovation through reduced credit supply. Additionally, it should be noted that the current article employs data at annual frequency and hence deviates from the norm of taking 5 year averages of the variables [e.g. in Levine et al. (2000) and Cecchetti and Kharroubi (2012)]. This is done not only to emphasize the short run effects but to gain from maximum variation in data. It is proposed that to capture long-run relationship, long-run elasticities should be computed instead of throwing away useful time variation in data by averaging 5 year intervals and hence greatly reducing the time dimension.

As innovation is considered to be the main driver in the growth process by economists and historians alike [See Mokyr (1990) and Solow (1957)]. The results of the article contributes to our understanding of how an effective financial system affects long run economic growth. This might have policy implications where innovation is explicitly considered in the design of policies surrounding financial markets. Furthermore, contrary to what is usually assumed; that the effect of finance on the real economy is felt in the long-run, the results here suggests a relatively quick propagation of effect of finance on innovation at least.

Lastly, it also becomes important to highlight the limitations of the study. Firstly, the future demand for credit and expectation formation is largely left out of the analysis. This might be particularly important for assessment of innovation-finance relationship in the context of capital markets. In an attempt to account for this, price indices (e.g. S&P Global Equity Indices) were included that turned out to be statistically insignificant across all estimators. An analysis that can explicitly account for expectation formation and future prices will help in gauging the validity of current results. Furthermore, the issue of endogeneity cannot be completely ruled out. Roodman (2009) notes the weakness of Sargan test of instrument validity for GMM estimators (due to large number of moment conditions). Although, instruments in compact form are used which mitigates this problem but the sheer number of instruments used in GMM estimators might make us falsely conclude that the errors in our equations are serially uncorrelated, again introducing the problem of endogeneity. It is also acknowledged that there is room for improvements in proxies for both supply and demand for credit. For example, it is possible that higher coefficient estimates of bank credit might be due to the fact that the particular proxy used for bank credit is better at capturing bank market credit supply relative to stock market credit supply effects[41]. Future research using alternative proxies and approaches, for example Mian and Sufi (2010) and Rajan and Zingales (1998a) methodology in identifying credit supply channel[42] would help in accessing the validity of the current results.

Appendices

A Data Description

The sample includes a broad cross section of countries [an unbalanced panel] composed of 76 countries from year 1988 to 2010[43]. Data are taken from World Development Indicators of the World Bank, Eurostat of the European Commission and International Financial Statistics and Financial Access Survey of IMF. The heuristic rule for elimination of country/year was based on the availability of at least one innovation measure, bank and capital market indicators, in addition to control variables.

[41]However, the use of GMM estimators here reduces this measurement error problem to some extent [See, Wansbeek (2001); Griliches and Hausman (1986)].

[42]Rajan and Zingales (1998a) evaluate whether industrial sectors that are more in need of external finance grow disproportionately faster in well developed financial markets.

[43]The time average in the preferred regression is 14.35 years for each country.

Table 11 Descriptive Statistics

Variables	Normalization	Source		Mean	Sd. Dev.	Min	Max	Obs
Patents	*GDP*	WDI	overall	6.7248	2.7404	0	13.62	N = 2890
			between		2.7058	1.3693	12.97	n = 85
			within		0.7704	0.5956	9.708	T = 34
EmpKnowIntenAct	*Labour Force*	Eurostat	overall	8.1834	1.73	10.977	9.549	N = 110
			between		1.8131	10.868	9.464	n = 10
			within		0.0852	8.4714	7.838	T = 11
RnDExp	*GDP*	WDI	overall	1.1989	0.9499	0.0161	4.803	N = 902
			between		0.9362	0.0214	4.08	n = 82
			within		0.184	0.1457	1.979	T = 11
Mar_Cap	*GDP*	S&P	overall	3.383	1.4317	5.4876	6.424	N = 1482
			between		1.3224	0.8529	5.621	n = 78
			within		0.8118	4.1304	6.107	T = 19
CreditbyBanks	*GDP*	IFS	overall	4.0357	0.7098	1.7155	5.794	N = 2964
			between		0.5747	2.52734	5.256	n = 76
			within		0.4631	1.64962	5.761	T = 39
GDP	*Tot. Population*	WDI	overall	8.3285	1.4765	4.28116	11.59	N = 3528
			between		1.4197	5.45056	11.14	n = 84
			within		0.3993	6.7927	10.33	T = 42
Unemployment	*Labour Force*	IFS	overall	1.891	0.6007	12.4245	3.594	N = 1701
			between		0.564	13.2598	3.468	n = 81
			within		0.323	15.7525	3.002	T = 21
CRDUM	*none*	see text	overall	0.043	0.204	0	1	N = 1870
			between		0.019	0.03846	0.125	n = 85
			within		0.203	0.0815	1.005	T = 22
BANKCRISES	*none*	see text	overall	0.011	0.106	0	1	N = 1870
			between		0.015	0	0.0769	n = 85
			within		0.105	0.065	0.9922	T = 22

The descriptive statistics of variables used in the regressions are given in Table 11. For most variables data is available for around 80 countries. However, for EmpKnowIntenAct[44] [Employment in Knowledge Intensive activities] data for only 10 countries is available. Therefore, this innovation measure is not utilized except in robustness checks, as they severely limit the sample size.

Furthermore, from Table 11 one can also see that there is substantial variation of data in the sample, both across countries and time. For example, market capitalization with the mean of 3.38 has across country standard deviation of 1.32 and across time deviation of 0.81. The proxy for demand for credit, GDP per capita, also displays wide variation. This also speaks about representatively of the sample where both developed and developing countries are part of the analysis. For example, USA with an average GDP per capita of US $ 33212.13 and Bangladesh with the average GDP per capita of US $ 372.45, are both part of the sample[45]. Measures of bank and capital market liquidity are included in the list of variables. For the bank market, logarithm of total credit provided by banks to the private sector as a percentage of GDP is used [CreditBanks][46], while for capital market the logarithm of market capitalization as a percentage of GDP [total value of tradable shares in the country] is used as a proxy for capital market lending [MarCap]. To access the impact of crisis on innovation, a crisis dummy is generated and included among the set of explanatory variables. It takes value of 1 in crisis years of 2008 and 2009.

Moreover, a country specific banking crisis dummy variable [BANKCRISES] is created that takes the value of 1 in the peak year of banking crisis in a particular country. An event is identified as a crisis year in particular country according to Kaminsky and Reinhart (1999) categorization. Post 1997 crises are taken from Reinhart and Rogoff (2008). Particularly, the "Big 5 Crises" that followed a drop of 5% in GDP growth from trend are included. When it was not possible to determine the peak year, middle year(s) of the crisis is taken as peak. The addition of this variable allows to more accurately access the impact of access to finance and innovation as various structural breaks and deviation from long-run means at times of crises are directly taken into account.

All variables except dummies are in natural logarithms. Hence, the estimated equations take log-log form, and we get simple percentage interpretations in our regressions. Additionally, all except the base line innovation

[44] See Eurostat website for more details.

[45] See appendix B for full list of countries.

[46] The measure is all domestic credit provided by banking sector on a gross basis with the exception of credit to the government.

variable are normalized to account for country size effects. Innovation is not normalized based on the "Growth without scale effects" literature. Normalized innovation measures do not change the results in any significant way [see section 5 and Table 10]. Conventional wisdom would let one to believe that as scale of an economy increases, so does the quantity of rents captured by successful innovators which creates a higher incentive to innovate in large vis-a-vis small economies. However, as Jones (1995) has shown, that this is inconsistent with post-world war evidence for the OECD countries, where larger countries did not innovate and hence grow faster than smaller countries. Young (1998) explains this theoretically by arguing that an ever increasing product variety as a result of larger economy spreads innovation across more and more individuals and hence the larger set of products require larger research input for further innovation. Particularly, reward from greater population is nullified by rising product proliferation and increased complexity of close to the frontier innovations that counters the large market available for entrepreneurs, thus preventing the rise in reward for innovation with greater population. One should also note that though the semi-endogenous growth theory differ from the new Schumpeterian theory in their sources of long-run growth, they are in agreement about the absence of scale effects [see Laincz and Peretto (2006) and Aghion and Howitt (2005) for more empirical evidence][47].

B Variance Decomposition

As GMM estimators do not directly compute R-squares [because of instrumentation], a different approach for variance decomposition was needed. A slight variant of the correlated variance share [CVS] approach is applied, where variation of individual explanatory variables are normalized by variation of fitted values of dependent variable [See Gibbons et al. (2012)]. First, the following algorithm to obtain fitted values from equation (10) is applied[48]:

$$\widehat{GDP} = \beta_j \cdot GDP + \beta_k \cdot L.GDP$$

$$\widehat{Unemployment} = \beta_l \cdot Unemployment + \beta_m \cdot L.Unemployment$$

$\widehat{\text{CREDITBANKS}} =$
$\beta_n \cdot \text{CREDITBANKS} + \beta_o \cdot L.\text{CREDITBANKS} + \beta_p \cdot L2.\text{CREDITBANKS}$

[47]For alternative theoretical expositions for the absence of scale effects, see Peretto and Smulders (2002); Howitt (1999).

[48]j is an index that takes a different value for each coefficient.

and so on ...

Variances are calculated for the fitted values of each explanatory variable which is normalized by the variances of the fitted values of dependent variable. For example, to access the contribution of GDP:

var $[\widehat{GDP}]$/ var $[\widehat{Patents}]$ where, var represents corresponding variances.

This methodology is useful as it not only exploits the full explained contribution of regressors in the estimated equation but also is based on the full estimated equation. This is in contrast to R-squared measures of variances and partial sum of squares methods as ANOVA, which are based on nested models, and where only the contribution uncorrelated with the fixed effects can be extracted.

C Full List of Countries

Argentina	Czech Rep	Iceland	Malta	Singapore
Armenia	Germany	Israel	Malaysia	El Salvador
Australia	Denmark	Italy	Mayotte	Serbia
Austria	Egypt	Jordan	Netherlands	Slovak Rep
Belgium	Spain	Japan	Norway	Slovenia
Bangladesh	Finland	Kenya	New Zealand	Sweden
Bulgaria	France	Kyrgyz Rep	Pakistan	Sint Maarten
Bosnia and Herzegovia	United Kingdom	South Korea	Peru	Thailand
Brazil	Georgia	Lithuania	Philippines	Tajikistan
Canada	Greece	Luxemburg	Poland	Turkey
Switzerland	Hong Kong	Latvia	North Korea	Ukraine
Chile	Croatia	Marshall Islands	Portugal	Uruguay
China	Hungary	Moldova	Paraguay	United States
Columbia	India	Madagascar	Romania	Uzbekistan
Cyprus	Ireland	Mexico	Russia	Vietnam
South Africa				

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