Which Way to Go Now? Financing Economic Growth in the Sustainable Development Era

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Our paper uses a novel methodology to reexamine the relationship between financial development and economic growth in the era of sustainable development. Our empirical procedure deals with both functional-form misspecification bias as well as bias from endogenous regressors. It also provides an estimate of the growth–finance relationship for every country-year observation, allowing us to examine the relationship of interest for various country groups, using a global sample of 133 countries during 1960–2015. Our results indicate that countries with weak institutions and a smaller-than-average banking sector will reap more benefits from bank-based financial systems. The impact of financial development on economic performance has enormous policy implications for international institutions that provide policy support to countries in their pursuit of achieving the 2030 Agenda for Sustainable Development.

Keywords: economic growth, financial development, nonlinearities, nonparametric methods

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I. Introduction

Is credit a banker's gift to the world or are strong institutions a government's gift to its citizens? Does financial development always lead to economic growth or is the relationship dependent on the definition of financial development, country characteristics, as well as the quality of institutions? These questions are increasingly gaining importance in the era of sustainable development. This paper uses nonparametric kernel regression estimates to find answers.

Literature on the impact of financial development on economic growth is vast, extending over decades, originating from the Schumpeterian (Schumpeter 1934) view of credit being a banker's gift to humanity (King and Levine 1993). Levine (2005) provides a nice overview of the theoretical as well as empirical literature on this topic. Most theoretical papers support a positive link between financial development and economic growth; however, the mechanism of influencing growth is where they differ in opinion. Irrespective of the actual mechanism of influence, most agree that the outcome will be in improving the distribution of resources via the allocation of capital to users who value it most. Law and Singh (2014) provide a summary table of empirical results from recent papers, where findings are mixed depending on the definition of financial development, methodology, and sample. The size and composition of financial institutions play a crucial role in boosting economic performance, and yet they tell only a part of the story. Other papers such as Acemoglu, Johnson, and Robinson (2001); Sachs (2003); Easterly and Levine (2003); Rodrik, Subramanian, and Trebbi (2004); and Basu and Das (2016) evaluate the importance of efficient domestic institutional conditions, human capital accumulation, and geography on the growth–finance relationship.

These papers do not settle the issue of causality. Financial development induces faster economic growth by allocating resources more efficiently, allowing more rapid accumulation of physical and human capital, and accelerating technological innovation. The reverse is also true. Economic growth leads to increased demand for financial services and more financial development. This bidirectional causation makes financial development endogenous and ordinary least squares estimates biased. Papers like Levine, Loayza, and Beck (2000) with traditional parametric models handle the issue of causality by estimating different generalized method of moments (GMM) and system GMM models on a panel of 74 countries during 1960–1995 (over 5-year averages). In the first GMM panel regression, they apply the methodology of Arellano and Bond (1991), difference the regression equation to remove any omitted variable bias created by unobserved country-specific effects, and then instrument the differenced right-hand side variables using lagged values of the original regressors.

To improve the efficiency of their estimates in a system GMM regression, they apply the methodology of Arellano and Bover (1995) and instrument the right-hand side variables with lagged differences of the original regressors. Levine, Loayza, and Beck (2000) conclude that the exogenous component of financial intermediary development is positively associated with economic growth. Benhabib and Spiegel (2000) apply similar procedures and draw a similar conclusion; their results are sensitive to the definition of financial development and inclusion of country-specific fixed effects.

These GMM estimators are very effective in dealing with bias caused by endogenous regressors; however, they are designed only for parametric models. This paper uses a nonparametric kernel regression methodology to estimate how financial development influences growth at the cross-country level during 1960–2015 (with 5-year averages). Papers applying nonparametric methods to growth data acknowledge the devastating impact of functional-form misspecification on policy prescriptions and a general understanding of economic relationships (Liu and Stengos 1999; Durlauf, Kourtellos, and Minkin 2001; Maasoumi, Racine, and Stengos 2007; Henderson, Papageorgiou, and Parmeter 2012). The nonparametric methodology gives us a consistent estimate of the growth–finance relationship when the underlying functional form of the regression function is unknown, thus avoiding functional-form misspecification bias, a major benefit of using this technique.

Certain nonparametric estimates, such as local linear least squares (LLLS), are great at handling functional-form misspecification bias but terrible at dealing with bias generated by endogenous regressors. To deal with this issue, Su and Ullah (2008) modify the nonparametric kernel regression methodology for models with endogenous regressors. The paper by Henderson, Papageorgiou, and Parmeter (2013) is the first one to apply Su and Ullah's methodology to account for endogeneity in a growth–finance relationship in a fully nonparametric framework. They state a need to spread awareness about this new approach, and our paper is another attempt to try to spread the word. We update their data set (adding another measure of financial development) and use Su and Ullah's methodology to examine the growth–finance relationship for various country subsets (not considered by them). We hope to demonstrate the ease of applying this new methodology and suggest that other data practitioners consider their approach.

In 2015, 193 member states of the United Nations (UN) included a financing-for-development framework in the 2030 Agenda for Sustainable Development. Development of the financial sector is a key element of the financing-for-development framework. Depending on various regional specificities, research shows that market-based financing (e.g., stock market turnover ratio) has been growing steadily, more than bank-based financing (e.g., share of deposit money banks assets in total assets), particularly in Asia and the Pacific (Basu and Xu 2015). Nonparametric models are particularly suited to evaluate this trend as we get an estimate of the slope of the regression function ($\Delta\gamma/\Delta X$) at every data point (i.e., for every country-time observation), which allows us to determine how the growth–finance relationship varies among different country groups based on institutional quality, level of development, and geographical features. Our paper takes a closer look at these recent trends about bank-based financing (particularly in vulnerable country groups) to evaluate their desirability. We revisit the discussion on financial development and growth for vulnerable country groups, particularly in Asia and the Pacific.

We find that the partial impact on economic growth is smaller using a measure of financial development that is market based versus one which is bank based. This result holds true for all country groups. We infer policy makers' preference for a bank-based over a market-based measure of financial development from our nonparametric estimates, which correct for functional-form misspecification bias as well as endogeneity bias. Institutions play a vital role in how financial development influences economic growth. For countries with weak institutions, the distribution of estimates of the partial impact of bank-based financial development on economic growth is to the right of the distribution of estimates of the partial impact of market-based financial development on economic growth. Countries with weak institutions experience more growth under bank-based systems. Those with strong institutions show more growth under market-based financial systems. Our findings caution against the recent trends of countries moving resources away from bank-based measures of financial development to market-based measures. Our findings also lead us to suggest that countries pay attention to the quality of institutions, while diverting resources for growth; in the absence of good institutions, bank-based financial development can have a greater positive impact on economic growth.

We acknowledge that our work has some limitations. Nonparametric methods correct bias from functional-form misspecification and can be adjusted to correct bias from endogenous regressors. However, nonparametric model specifications suffer from the curse of dimensionality, which refers to the difficulty in determining the structure of high-dimension, data-generating processes without excessive parametric assumptions (Henderson and Parmeter 2015). Following the lead of Henderson, Papageorgiou, and Parmeter (2013), to avoid overfitting, we leave out some regressors included in parametric specifications in other papers. We acknowledge this is a limitation of our approach and leave to future works the estimation of a semiparametric model, in which more regressors along with time and country dummies can appear, in a parametric relationship with economic growth in the same model where economic growth has a nonparametric relationship with financial development.

The rest of our paper has the following structure. Section II reviews the relevant literature. We discuss our data and sources in section III. Section IV explains the nonparametric two-stage least squares (2SLS) method for dealing with bias generated by functional-form misspecification and by endogenous regressors. In section V, we discuss our results in the context of current literature. Section VI concludes with policy recommendations and the future directions of our work.

II. Literature Review

In traditional macroeconomic theory, financial sector development and capital accumulation are intertwined. In particular, an improvement in the financial market can produce positive outcomes by reducing the loss of resources required to allocate capital, increasing the capital–saving ratio and raising capital productivity. Development of the financial sector therefore contributes to capital accumulation that subsequently ensures robust economic growth. It also helps to increase productivity by selecting the most profitable investment projects.

A country's financial system can take the form of either a bank-based or a market-based system (Ergungor 2004). In the bank-dominated financial system, banks have the dominant role in mobilizing resources, identifying bankable projects, managing risks, and incentivizing technological progress and innovation. On the other hand, with the market-dominated financial system, market operations provide the necessary lead in identifying investment portfolios, devising risk management activities, and supporting high-risk high-return projects, thus reducing the inherent inefficiencies associated with bank-based financing systems.

King and Levine (1993) present cross-country evidence of a positive relationship between bank-based measures of financial development and economic growth via the mechanism of physical capital accumulation and growth of economic efficiencies, using data from 80 countries from 1960 to 1989, after controlling for numerous country and policy characteristics. Furthermore, Levine and Zervos (1998) show that both stock market liquidity and banking development positively predict growth, capital accumulation, and productivity improvements, even after controlling for economic and political factors, in 47 countries from 1976 to 1993. These papers do not deal with bias from endogenous regressors. To correct that bias, Levine, Loayza, and Beck (2000) estimate a GMM dynamic panel model with data from 74 countries, averaged over 5-year intervals during 1960–1995, and find that legal and accounting reforms can boost financial development, which can accelerate economic growth. These papers find a positive linear relationship between economic growth, financial development, and the quality of institutions in linear parametric models.

Other papers in the literature try to bring out nonlinearities in the growth–finance relationship. Deidda and Fattouh (2002) find different results for high- and low-income countries, while Rioja and Valev (2004) find that the growth–finance relationship depends on the country's level of financial development. Shen and Lee (2006) find an inverse U-shaped relationship between stock market variables and economic growth, while Ergungor (2008) finds that countries with an inflexible judicial system grow faster under a bank-based financial system, thus hinting at the importance of institutions in determining the growth–finance relationship. Cecchetti and Kharroubi (2012) conclude that bank-based financial development can be too much of a good thing for a country's growth by rigorously estimating a nonlinear inverted U-shaped relationship. Law and Singh (2014) provide evidence on banking sector development benefiting growth only up to a certain threshold, after which more development affects growth adversely. They provide a summary table of results from the most recent articles, which find a nonlinear relationship between growth and finance. These papers use parametric models to draw inferences. Henderson, Papageorgiou, and Parmeter (2013) deal with bias from endogenous regressors in a growth–finance relationship in a fully nonparametric framework. They look at the impact of only bank-based financial development on economic growth and find that the relationship benefits developed countries the most, while low-income countries do not benefit at all. Basu and Das (2016) provide nonparametric LLLS estimates, which find a positive impact of both bank- and market-based financial development on gross domestic product (GDP) per capita, irrespective of the size of the financial sector, for various United Nations regional classifications. However, they do not correct for the endogeneity of regressors.

Easterly, Islam, and Stiglitz (2000) take a different view than we do and find that financial development is desirable up to a point. They find that financial systems that feature debt more prominently than equity are more vulnerable to growth collapses. Papers like Basu and Xu (2015) bring up the importance of the composition of the financial sector in a country; they note the alarming steering of the financial structure toward market-based approaches in a number of countries in Asia and the Pacific such as Australia, India, Indonesia, Japan, and the People's Republic of China. Contrary to Easterly, Islam, and Stiglitz (2000), they observe that countries with primarily bank-based financing systems fared better during the global financial crisis. They also caution that the impact of financing on economic growth may be dependent on the size of the financial sector and the level of development, a warning aimed at countries with specific geographical limitations or development challenges.

With the growth of financial services around the world, many argue that property rights, the rule of law, and institutional quality play an important role in improving the effectiveness of the financial system in facilitating the economic growth process. Some authors like La Porta et al. (1996) hold the view that financial development depends on the rights and privileges given to investors, shareholders, and creditors by the legal institutions of a country. Strong property rights being closely related with financial development and growth is emphasized by other authors such as Beck, Demirgüç-Kunt, and Levine (2002); Claessens and Laeven (2003); and Beck et al. (2008). Levine and Demirgüç-Kunt (2001) use data from 48 countries for three indicators for the legal system—creditor, antidirector, and rule of law—as instruments for financial development, finding evidence supporting the importance of financial services and the law. Others like Easterly and Levine (2003) and Rodrik, Subramanian, and Trebbi (2004) emphasize the impact of the quality of institutions on growth, while Sachs (2003) suggests that germ ecology directly affects per capita income after controlling for institutions. Basu and Das (2010) find a positive impact of institutional quality on developmental quality based on local linear nonparametric and semiparametric estimates.

This broad spectrum of work suggests that institutions, level of development, and geographical factors influence the functioning of the financial system and the growth–finance relationship. Thus, our work uses a kernel-based nonparametric estimation technique to deal with endogenous regressors and estimates a growth–finance relationship for countries grouped by level of development, geographical features, and quality of institutions. Several countries in Asia and the Pacific face special development challenges. Collectively, we refer to these countries as countries with special needs (CSNs) as they are either least developed countries (LDCs), landlocked developing countries (LLDCs), or small island developing states (SIDS). The isolation from world markets faced by LLDCs, the lack of economies of scale in SIDS, and the lack of productive capacities faced by LDCs are some of the unique challenges experienced by these vulnerable countries. We use our nonparametric estimates to comment on how these CSNs benefit from financial development. Addressing the challenges they face is critical for sustaining their development as well as pursuing the 2030 Agenda for Sustainable Development.

There are some methodological and sample differences between our paper and similar ones in the literature. Deidda and Fattouh (2002) estimate a parametric threshold model with least squares methodology. Their data set covers 119 countries over the period 1960–1989. They do not account for bias from functional-form misspecification or endogenous regressors. Henderson, Papageorgiou, and Parmeter (2013) account for these biases and evaluate the growth–finance relationship only for bank-based measures of financial development. Their data set covers 101 countries over the period 1960–2000. We take a cue from Basu and Xu (2015), who warn against Asia and the Pacific's alarming bias toward market-based approaches, and consider both bank-based and market-based measures of financial development for comparison. Our results indicate that progrowth policy makers of all countries will prefer measures of financial development that are bank based to those that are market based. Henderson, Papageorgiou, and Parmeter (2013) conclude that Organisation for Economic Co-operation and Development countries benefit from bank-based financial development, while non-Organisation for Economic Co-operation and Development countries do not benefit at all. We use the same methodology on an updated data set with more countries and years, extend their analysis to other country groups, and find that the positive relationship between growth and bank-based financial development is particularly applicable to vulnerable countries facing special challenges (e.g., SIDS, LLDCs, and LDCs, as well as heavily indebted poor countries [HIPCs]), including many countries in Asia and the Pacific.

III. Data

Table A5.9 presents select papers in the empirical literature and includes the various country groups and time periods they consider. Our paper employs an unbalanced panel data of 133 countries during 1960–2015.[1] Tables A5.7 and A5.8 provide a list of countries appearing in different country groups (e.g., groups determined by level of development or geography) and select descriptive statistics by group. In line with the growth–finance literature, we average the data set over 5-year periods, which tends to smooth business cycle effects.

In our paper, typical growth variables are motivated by Solow's (1956) model and obtained from Durlauf, Kourtellos, and Tan (2008). These are average annual growth rate of real GDP per capita (measured in 2011 United States dollars) or economic growth (*ecogr*), initial GDP per capita or γ_0, average investment (% of GDP) or *Inv*, and average annual growth rate of the working-age population (i.e., 16–64 years old) or *Popgr*. We refer to the World Development Indicators for *Popgr* data. We obtain the rest from version 9.1 of the Penn World Tables (PWT).[2] There are several advantages of using the "next generation" version of PWT over older versions. New PWT distinguish between GDP measured from the expenditure side and the production side, thus allowing us to compare productive capacities across countries. Moreover, new

[1] Data for market-based measures begin from 1975 and therefore are a smaller subset.
[2] For a description of data and variables, we refer to Feenstra, Inklaar, and Timmer (2015).

PWT calculate real GDP using prices that are constant across countries and over time, thus creating a distinction between real and current GDP and correcting for inflation.[3]

We refer to Barro and Lee (2013) for data on education or *Edu* (share of working-age population 15–64 years with a primary education) as a reasonable proxy for a country's stock of human capital. They construct their data set at 5-year intervals from 1950 to 2010.[4] Financial development variables are from the Financial Structure Dataset maintained and updated by the World Bank. Not all measures of financial development are available for all countries at all years, which does limit our choice. We use the following six measures of financial development:[5]

- *PrivY* defined as private credit by deposit money banks/GDP (%);
- *Bank* defined as deposit money banks assets/(deposit money + central) bank assets (%);
- *Depth* is deposit money banks' assets/GDP (%);
- *Stability* is private credit by deposit money bank/bank assets (%);
- *Stock* is total value of shares traded/average market capitalization (%);[6] and
- *Other* is bank deposits/GDP (%).

Ergungor (2004) explains why in some countries firms look to banks for financing, while in others they look mainly to financial markets to meet their financial needs. His explanation is tied to the country's legal system. Ergungor (2008) finds that banks as relationship lenders are vital for economic growth in an inflexible judicial environment because they assume additional roles to compensate for the inflexibility of the judicial system. This result holds even after controlling for legal origin and how well the laws are drafted and enforced. As flexibility increases, this role becomes less critical and the advantage of a bank-based system disappears. This finding is different from the one in earlier papers which argues that relationship-based systems are superior to market-based systems in environments where laws are poorly drafted and enforced (Rajan and Zingales 1998). To determine the impact of bank-based and market-based financial development on economic growth, we follow definitions in Ergungor (2004), who measures bank orientation by bank loans to the private sector, or *Bank*, and market orientation by stock market capitalization, or *Stock*.

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[3] Following the lead of Henderson, Papageorgiou, and Parmeter (2013), we leave out regressors that measure openness and government consumption to avoid overfitting (cross-validation is known to overfit a model).

[4] To make their data compatible with data from other sources, we assume the value of *Edu* in 2010 and 2015 are the same.

[5] We accessed the Global Financial Development and World Development Indicators databases on 15 October 2019.

[6] This is also known as the stock market turnover ratio.

Merging macrodata from various sources with data on *Bank* gives us an unbalanced 5-year nonoverlapping panel data set, which includes 1,155 country-year observations with 133 countries during 1960–2015. We retain fewer observations when merging with data on *Stock*, giving us an unbalanced 5-year nonoverlapping panel data set of 507 observations on 100 countries during 1975–2015.[7]

We convert to ratios (dividing by 100) all financial development variables (*Bank*, *Stock*, *PrivY*, *Stability*, *Depth*, *Other*) along with *Inv*, *Edu* and then take natural logs of those ratios. The dependent variable *ecogr* along with *Popgr* are percentages. This makes our models a nonparametric version of the parametric semilog model. When $ecogr = m(x)$, then $\beta(x)$ is a partial derivative of $m(x)$ with respect to x. Nonparametric methods give us an estimate of $\beta(x)$ for every observation. Here, when x increases by 1%, *ecogr* changes by $\beta(x)$%.

In our model (1), we estimate a nonparametric relationship between *ecogr* and *Bank*, where *Bank* measures financial development using a global sample of 1,155 country-year observations with 133 countries during 1960–2015. In model (2), we estimate a relationship between *ecogr* and *Stock*, where *Stock* measures financial development using 507 observations on 100 countries during 1975–2015. The nonparametric estimation process gives us 1,155 estimates of $\frac{\partial ecogr}{\partial Bank}$ and 507 estimates of $\frac{\partial ecogr}{\partial Stock}$, which we are happy to share with readers upon request. To make distributions of $\frac{\partial ecogr}{\partial Bank}$ and $\frac{\partial ecogr}{\partial Stock}$ comparable, we look at 480 country-year observations with common data on both *Bank* and *Stock*.

IV. Empirical Methodology

Parametric methodology is the most commonly applied methodology in the growth–finance literature, although recent papers also apply nonparametric and semiparametric techniques. We place in Appendices 1–4 a brief summary of the parametric and nonparametric estimation procedures: local-constant least squares (LCLS) and LLLS regressions. In this section, we discuss the LLLS regression with one endogenous regressor.

Nonparametric estimates are successfully able to handle bias created due to functional-form misspecification; however, they are not as successful when it comes to bias created by endogenous regressors. Many papers in the literature such as Newey

[7] For all data sets, the STATA and R codes used in the empirical estimation are available from the authors upon request.

and Powell (2003), Hall and Horowitz (2005), and Darolles et al. (2011) try to fill this gap. Su and Ullah (2008) develop a nonparametric estimator, which can handle endogenous regressors in a kernel function framework. The paper by Henderson, Papageorgiou, and Parmeter (2013) was the first paper to apply this methodology to estimate the growth–finance relationship. They stated a need to spread awareness about this new methodology, and our paper is another step in that direction.

Following the discussion in Su and Ullah (2008), we consider equation (1), with a single endogenous regressor:

$$y_i = m(x_i, z_{1i}) + \varepsilon_i, \tag{1}$$

$$x_i = g(z_i) + u_i. \tag{2}$$

In this system that equations (1) and (2) represent, y_i is a dependent variable; $m(\cdot)$ is an unknown smooth function of interest; x_i is an endogenous regressor; $z_i = (z_{1i}, z_{2i})$, where z_{1i} and z_{2i} are vectors of exogenous variables and instrumental variables, respectively; $g(\cdot)$ is an unknown smooth function of the instrument z; and u and ε are disturbances. It is assumed that $E(u|z) = 0$ and $E(\varepsilon|z, u) = E(\varepsilon|u)$. These assumptions are less restrictive as they allow errors to be heteroskedastic. In our paper, in equations (1) and (2), the dependent variable (*ecogr*) is an unknown function $m(z_1, x)$ of z_1 and x, where $z_1 = [1\text{n}(Y_0), Popgr, Inv, Edu]$, and x is some measure of financial development. This measure is *Bank* in model (1) and *Stock* in model (2). Other measures of financial development, *PrivY* and *Depth* are instruments (z_2) for *Bank*; *PrivY* is an instrument for *Stock*. We discuss our reasoning for the choice of instruments in section V. All variables except *ecogr* and *Popgr* are in log format.

Su and Ullah's (2008) method is a nonparametric 2SLS process. The first stage requires a nonparametric regression of the endogenous regressor on all exogenous (z_{1i}) and instrumental variables (z_{2i}) in equation (2). The second stage requires the nonparametric regression of the y variable on each of the regressors in equation (1), including the endogenous regressor x_i (not a predictor of it) and the residuals from the first stage. Then, we obtain consistent nonparametric 2SLS estimates of $\hat{m}(x, z_1)$ by averaging a counterfactual estimate obtained in the previous step.[8] This nonparametric procedure gives us an estimate of $m(x)$ and the slope coefficient ($m'(x)$ or $\beta(x)$) for every country-time observation in our data set.

As suggested by Su and Ullah (2008), the first stage involves a local p_1—polynomial regression with a kernel function, K_h, and a bandwidth vector, h_1; and the second stage involves a local p_2—polynomial regression with a kernel function, K_{h2},

[8] $\hat{m}(x_j, z_{1j}) = \hat{w}(x_j, z_{1j}, \hat{u}_1) + \hat{w}(x_j, z_{1j}, \hat{u}_2) + \cdots + \hat{w}(x_j, z_{1j}, \hat{u}_n)$.

and a bandwidth vector, h_2. Bandwidth estimation is crucial in both stages, and Su and Ullah (2008) suggest a simple approach of data-driven bandwidth selection. For the choice of polynomial order, we refer to Henderson and Parmeter (2015), who provide simulation results to suggest $p_1 = 3$ and $p_2 = 1$ for consistency.[9]

We employ the methodology used by Henderson, Papageorgiou, and Parmeter (2013) to pick instruments in a nonparametric framework. When the bandwidth on a regressor hits its upper bound in an LCLS regression, as discussed in Appendix 3, that variable is deemed not to be a predictor of the dependent variable. Thus, we can use an LCLS regression of y on all potential regressors from the relevant model to determine which variables (in our case, which measure of financial development) are unrelated to y (in our case, economic growth). These can then be used as instruments in the first-stage regression in equation (2). For future works, we could also employ other instruments, frequently used in the literature, such as lagged values of the regressors. We encourage the reader to refer to Henderson, Papageorgiou, and Parmeter (2013) as well as Henderson and Parmeter (2015) for a discussion on other ways to handle endogenous regressors in a nonparametric setting. We concur with Henderson, Papageorgiou, and Parmeter (2013) about the simplicity and ease of applicability of Su and Ullah's (2008) methodology.

V. Nonparametric Estimates

A benefit of using nonparametric methods is that they give us an estimate of $\partial y/\partial x$ for every country-period observation in our data set. The challenge is in the presentation of these results, which we do in three ways. In Figures 1–5, we illustrate the distribution of nonparametric estimates of $\frac{\partial ecogr}{\partial Bank}$ and $\frac{\partial ecogr}{\partial Stock}$ by several criteria. We also implement a consistent integrated squared difference test for equality of densities as described in Li, Maasoumi, and Racine (2009). We present their test statistic (T_n) and corresponding p-value below all density graphs in Figures 1–5. In Table A5.2, we present first (Q1), second (Q2), and third (Q3) quartiles of all nonparametric estimates of $\partial y/\partial x$ for all endogenous and exogenous x in equation (1). In Tables A5.3–A5.6, we present the median nonparametric estimates of $\frac{\partial ecogr}{\partial Bank}$ and $\frac{\partial ecogr}{\partial Stock}$ in subgroups based on geography, level of development, quality of institutions, and size of the financial sector. We focus on the impact of endogenous financial development on economic

[9]For local p_1—polynomial regression, $p_1 = 0$ for LCLS estimates and $p_1 = 1$ for LLLS estimates. To get estimates from nonparametric models with endogenous regressors, we apply R codes available in Henderson and Parmeter (2015) and R's np package developed by Jeffrey Racine/R-Package-np.

growth in Figures 1–5 and Tables A5.3–A5.6 to compare bank-based and market-based measures of financial development.

We discuss estimates obtained from nonparametric regression under various subsections. First, we discuss the implications of bandwidth estimates for two model specifications. Next, we discuss the implications of controlling for endogeneity in our model. Finally, we describe how partial effects from our nonparametric model vary across country subsets.

A. Bandwidths

As discussed in Appendix 3, the choice of bandwidths for all regressors is critical for nonparametric estimation. Small bandwidths lead to under-smoothing and imprecise estimates, while large bandwidths lead to over-smoothing and biased estimates. We adopt the popular solution of determining optimal bandwidths by minimizing a cross-validation function. The bandwidths not only affect the degree of smoothing but also provide some indication of how the left-hand side variable is affected by the regressors. Cross-validation gives us high bandwidths for irrelevant regressors (Hall, Li, and Racine 2007); for practical purposes, a high bandwidth is at least two times the corresponding regressor's standard deviation. Irrelevant regressors are potential instruments for endogenous variables in the model (Henderson and Parmeter 2015). In addition, we employ consistent tests of significance of an explanatory variable or variables in a nonparametric regression setting that is analogous to a simple *t*-test or *F*-test in a parametric regression setting (as discussed in Racine, Hart, and Li [2006]). We fail to reject the null that *PrivY* and *Depth* are jointly irrelevant using bandwidths from applying the LLLS regression (*p*-value = 0.11) to equation (1), where *Bank* measures financial development. When *Stock* measures financial development in equation (1), we fail to reject the null hypothesis that *PrivY* is irrelevant (*p*-value = 0.356).

Table A5.1 presents local-constant, cross-validated bandwidths for equations (1) and (2) along with an upper bound for the bandwidth of every regressor in each model. For practical purposes, we list two times the standard deviation of each regressor as an upper bound, as done by Henderson, Papageorgiou, and Parmeter (2013) and Hall, Li, and Racine (2007). A variable is irrelevant when a bandwidth reaches its upper bound in the LCLS framework (or $BW_i \geq UB_i$). Comparing *UB* and *BW* indicates *Bank* from model (1) and *Stock* from model (2) are relevant financial development variables in predicting economic growth as $BW_i < UB_i$. At the same time, $BW_i > UB_i$ for other measures of financial development, which makes *PrivY* and *Depth* potential instruments for *Bank* in model (1); *PrivY* can be an instrument for *Stock* in model (2).

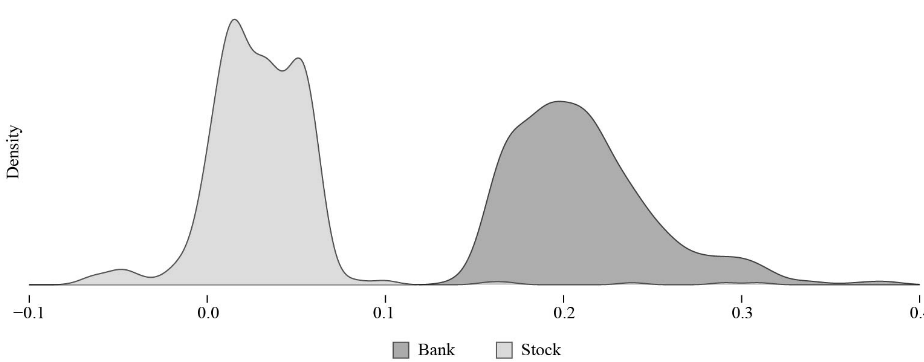
B. Baseline Estimates

In this section, we treat as endogenous the financial development variable in model (1) and model (2). We employ the methodology of Su and Ullah (2008) to obtain 2SLS estimates from a nonparametric model by estimating equations (1) and (2). The procedure gives us an estimate of the relationship between *ecogr* and every regressor *x* for every country-year observation. We get the standard errors of each estimate via bootstrapping. We then arrange in ascending order all estimates to identify the first, second, and third quartiles of these estimates along with their corresponding standard errors. Table A5.2 presents nonparametric 2SLS estimates of partial effects of all regressors on economic growth for models (1) and (2).

Following the lead of Henderson, Papageorgiou, and Parmeter (2013), we present nonparametric estimates corresponding to the 25th, 50th, and 75th percentiles of the distribution of our estimates (Q1, Q2, and Q3, respectively) along with their corresponding bootstrapped standard errors. To provide a visual display of the entire distribution of our nonparametric 2SLS estimates, we present nonparametric density plots in Figure 1. The distribution of estimates of $\frac{\partial ecogr}{\partial Bank}$ is clearly to the right of the distribution of estimates of $\frac{\partial ecogr}{\partial Stock}$.

First, we discuss estimated coefficients of nonfinancial regressors. For both models (1) and (2), the partial effects on economic growth by the initial income variable (Y_0) are negative and significant for all quartiles (Q1, Q2, and Q3). The negative significant coefficient of initial income (Y_0) is expected according to the convergence theory of Solow (1956). As is the case in traditional models, both *Inv*

Figure 1. **Distribution of Nonparametric Estimates of Coefficients by Type of Financial Development, All Countries**



Note: Null of equality of densities is rejected at the 1% level (test statistic $T_n = 402.96$, p-value = 0.00).
Source: Author's calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).

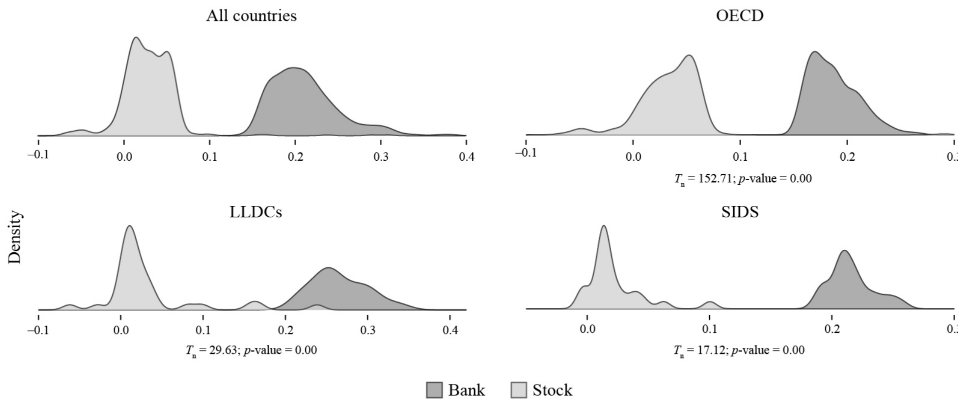
and *Edu* have a positive impact on economic growth; although for some quartiles, the estimates are not statistically significant. Likewise, for the population variable, *Popgr*, partial effects are statistically significant for all quartiles, although the magnitude is 0.

We now discuss partial impacts on economic growth by variables measuring financial development. For all quartiles, bank-based measures have a stronger positive impact on economic growth compared with market-based measures. Partial impacts of *Bank* on economic growth are significant and positive for Q1 (0.183), Q2 (0.206), and Q3 (0.233). Partial impacts of *Stock* on economic growth are positive for each quartile (Q1 = 0.013, Q2 = 0.029, and Q3 = 0.049), but they are not as high as those of *Bank* and are not statistically significant. Figure 1 presents density plots of estimated coefficients of *Bank* from model (1) and *Stock* from model (2). What we learn is similar to Henderson, Papageorgiou, and Parmeter (2013) and King and Levine (1993), who find that the relationship between economic growth and *Bank* is significant and positive. Our results for the relationship between economic growth and *Stock* are weaker than those obtained by Levine and Zervos (1998), who find that the relationship is positive and significant. We feel our results are similar to those of Law and Singh (2014), who find that financial development adversely affects growth beyond a certain threshold level. We think our nonparametric results will shed some light on how the slope coefficient estimates may change across various subgroups in the data—that is, the nature of the growth–finance relationship for different country groups.

C. Nonparametric Two-Stage Least Squares Partial Effects for Groups by Geography and Level of Development

Developing countries today may not replicate the historical growth and development experiences of developed countries. Relationships between economic growth and financial development that were observed in the developed world in the past may not hold in other country groups today. To highlight this, we provide the median of the distribution of nonparametric 2SLS estimates by country groups, determined by splitting our set of all estimates by geography (Table A5.3) and level of development (Table A5.4). We present only the median nonparametric estimates of $\frac{\partial ecogr}{\partial Bank}$ from model (1) and $\frac{\partial ecogr}{\partial Stock}$ from model (2). We are not reestimating our model for every country-group, instead we are using the full-sample estimated partial effects (we obtain one estimate for every observation) and obtaining median effects for each subgroup. To make distributions of estimates of $\frac{\partial ecogr}{\partial Bank}$ and $\frac{\partial ecogr}{\partial Stock}$ comparable, we look only at 480 country-year observations with common data on both *Bank* and *Stock*. To emphasize this point, the last two rows of Tables A5.3 and A5.4 provide information

Figure 2. **Distribution of Nonparametric Coefficients by Geography**



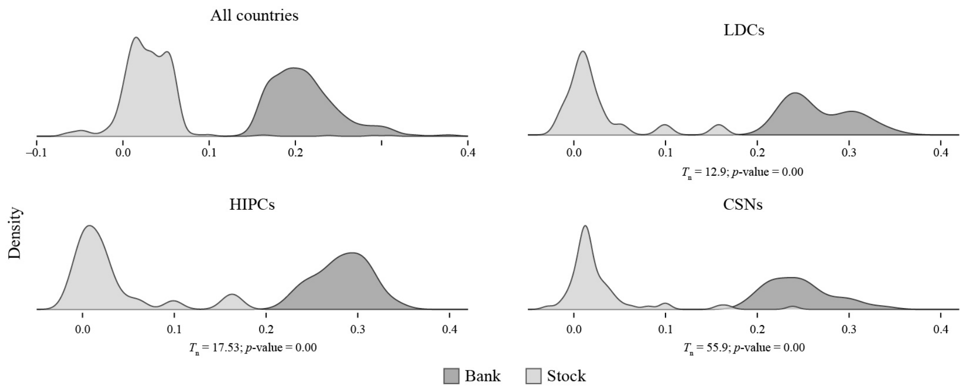
LLDCs = landlocked developing countries, OECD = Organisation for Economic Co-operation and Development, SIDS = small island developing states, T_n = test statistic.
Note: p-value < 0.01 implies we reject null of equality of densities at the 1% level.
Source: Author's calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).

on the number of observations used in the estimation and the number of observations actually in the subset; these two rows are not the same. We use bootstrapping to obtain standard errors of the median partial effects for each subgroup. We also present density plots of nonparametric estimates of $\frac{\partial ecogr}{\partial Bank}$ from model (1) and of $\frac{\partial ecogr}{\partial Stock}$ from model (2) for subsets based on geography in Figure 2 and level of development in Figure 3.

Tables A5.3 and A5.4 compare the Q2 of our nonparametric 2SLS estimates of the partial impact of financial development on economic growth across various subsets of countries. The bank-based measure of financial development (*Bank*) has a positive significant impact on economic growth for all subgroups, with LDCs and HIPCs showing the highest impact. Our results deviate a bit from the findings of Deidda and Fattouh (2002) and Henderson, Papageorgiou, and Parmeter (2013). According to their estimates, bank-based financial development has the most positive impact on economic growth in developed countries, while low-income countries do not benefit at all. We agree on financial development having a positive impact on economic growth in high-income developed countries. However, we also find that the partial impact of *Bank* on economic growth is positive and significant even in a low-income country group such as the LDCs, which have an average per capita income of $2,700 (Table A5.8).

The partial impact on economic growth is smaller by *Stock* than by *Bank*. This result holds true for all country groups. At the same time, the market-based measure

Figure 3. **Distribution of Nonparametric Coefficients by Level of Development**



CSNs = countries with special needs, HIPCs = heavily indebted poor countries, LDCs = less developed countries, T_n = test statistic.
Note: p-value < 0.01 implies we reject null of equality of densities at the 1% level.
Source: Author's calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).

of financial development (*Stock*) has a partial impact on economic growth, which is statistically insignificant for all subsets. Our nonparametric 2SLS estimates provide empirical support to Basu and Xu (2015), who caution against the rise of market-based financial systems in some country groups. Based on the results of our findings, we would advocate allocating resources to financial depth, particularly for HIPCs and CSNs, including the SIDS, LLDC, and LDC subgroups. To make this point visually, readers may look at distributions of coefficients of *Bank* and *Stock* for subsets of countries by geography in Figure 2 and by level of development in Figure 3. In each subset, we notice the density plot of $\frac{\partial ecogr}{\partial Stock}$ falls behind (to the left of) the plot of $\frac{\partial ecogr}{\partial Bank}$.

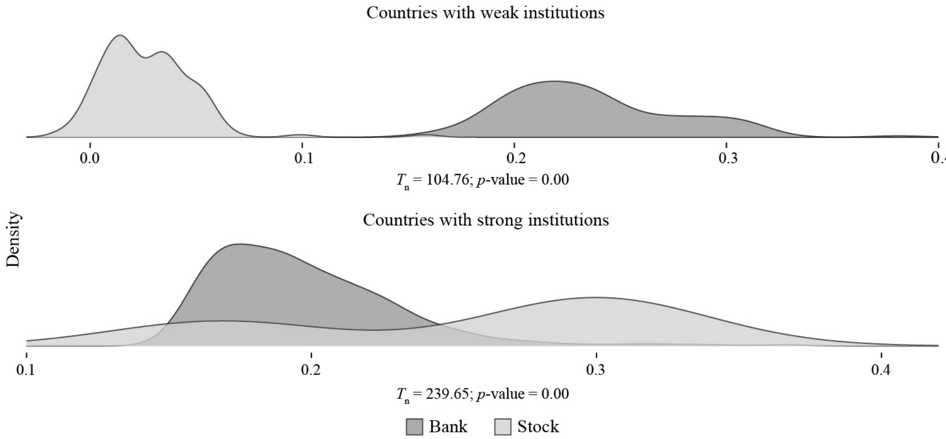
D. The Role of Institutions

An open banking environment fosters competition and efficient allocation of resources by expanding financing opportunities and promoting entrepreneurship. Transparency and reliable information make it possible for markets to provide dependable real-time information on prices, which rewards good decisions and penalizes bad ones. The importance of institutions in determining a growth–finance relationship is discussed by Ergungor (2008) and Miller, Kim, and Roberts (2018). According to Miller, Kim, and Roberts (2018), state regulatory activities going beyond the assurance of transparency and honesty in financial markets will discourage entrepreneurial activities and limit competition. They publish data on an index of financial freedom based on an annual data-driven research project. Unfortunately, the project starts from the year 1995, and index data for the years prior to 1995 are simply unavailable. To match with our data, which ranges from 1965 to 2015, we use an Index of Institutional Quality (IQI) developed in Basu and Das (2010).

Basu and Das (2010) construct the IQI from 23 indicators of quality spanning three aspects: economic, social, and political. Economic institutional quality is a combination of legal or property rights, bureaucratic quality, corruption, democratic accountability, government stability, law and order, independent judiciary, and regulation. Social institutional quality depends on press freedom, civil liberties, women's political rights, women's economic rights, and women's social rights. Political institutional quality depends on executive constraint, democracy, and political rights. The IQI ranges between 0.27 and 2.59 in our data set. A country with higher IQI value has stronger institutions. Readers may refer to Table A5.8 for the average values of IQI in various country subsets.

To make distributions of estimates of $\frac{\partial ecogr}{\partial Bank}$ and $\frac{\partial ecogr}{\partial Stock}$ comparable, we look only at 480 country-year observations with common data on both *Bank* and *Stock*. In Table A.5.5, we split this subset of 480 estimates into two groups by mean value of the IQI and present Q2 estimates for each group along with corresponding standard errors. We present the median partial impact of financial development (both bank- and market-based measures) on economic growth, for all country-year observations with lower-than-average IQI (this sample represents countries with weak institutions). Then we do the same for all country-year observations with higher-than-average IQI (i.e., for those countries with strong institutions). To see the entire distribution of nonparametric estimates, please refer to the nonparametric density plots in Figure 4. Here we present density plots of nonparametric estimates of $\frac{\partial ecogr}{\partial Bank}$ from model (1) and of $\frac{\partial ecogr}{\partial Stock}$ from model (2) for subsets based on quality of institutions. We see that countries with weak institutions perform better under bank-based financial systems—that is, the density plot of $\frac{\partial ecogr}{\partial Bank}$ for countries with weak institutions is to the right of the same plot for countries with strong institutions. In the same figure, we see that market-based systems are slightly better for those countries with strong institutions. We also implement a consistent integrated squared difference test for equality of densities as described in Li, Maasoumi, and Racine (2009). We present their test statistic and corresponding *p*-value below all density graphs in Figure 4. We reject the null hypothesis of equality of densities at the 1% level in both countries with weak institutions and countries with strong institutions. La Porta et al. (1996) and Levine and Demirgüç-Kunt (2001) find that the origin of a country's legal system, the ability of its institutions to adapt, and its economic growth are interconnected. Ergungor (2008) argues that in countries with inflexible judicial environments, the relationship-lending activities of banks become

Figure 4. **Distribution of Nonparametric Coefficients by Quality of Institutions**



T_n = test statistic.
Note: p-value < 0.01 implies we reject null of equality of densities at the 1% level.
Source: Authors' calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).

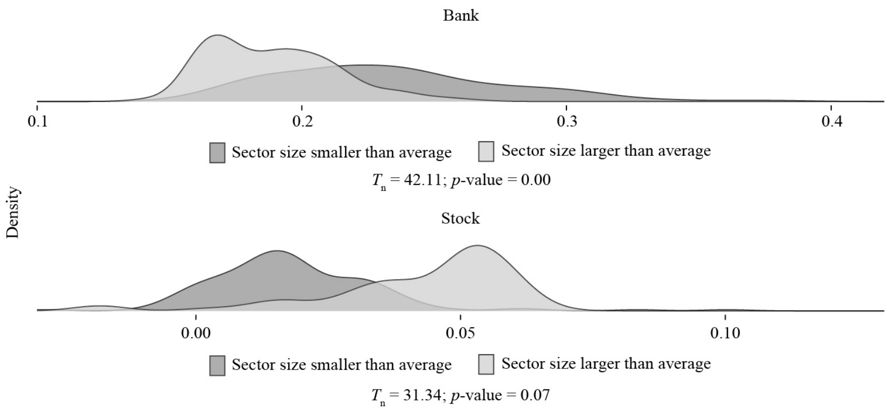
a vital engine for economic growth. Our findings support arguments made in these papers as we find that bank-based financial systems promote economic growth more than market-based financial systems in countries with weak and inflexible institutions.

E. Nonlinearities

Several papers in the literature highlight nonlinearities in the growth–finance relationship and find that it depends on the size of a country's financial sector (see Rioja and Valev [2004] and Shen and Lee [2006]). Many like Cecchetti and Kharroubi (2012) and Law and Singh (2014) conclude that financial development influences growth positively up to a certain threshold. To evaluate their claims, we split all nonparametric estimates from the global sample into two groups by average size of the financial sector. Again, we look only at 480 country-year observations with common data on both *Bank* and *Stock*. Table A5.6 presents the Q2 of all nonparametric estimates for each group. Figure 5 presents the complete nonparametric density plots of estimated $\frac{\partial ecogr}{\partial Bank}$ from model (1) and $\frac{\partial ecogr}{\partial Stock}$ from model (2) by the size of the financial sectors in these countries.

Figure 5 clearly illustrates that countries with a smaller-than-average banking sector perform better under bank-based financial systems compared with those countries who have a larger-than-average banking sector. The bank-based financial system shows diminishing returns to scale. The reverse is true for market-based

Figure 5. **Distribution of Nonparametric Coefficients by Size of Sector**



T_n = test statistic.
Note: p-value < 0.01 implies we reject null of equality of densities at the 1% level.
Source: Authors' calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).

financial systems. Countries with a larger-than-average, market-based financial system show more economic growth compared with those countries that have a smaller-than-average, market-based financial system. The market-based financial system shows increasing returns to scale.

Only for bank-based financial systems do our 2SLS estimates from a nonparametric model support the view of financial development affecting growth positively up until a threshold—that is, excessive financial development can be bad for economic growth. These findings lend support to nonlinearities in the growth–finance relationship discussed by several authors. This contradicts, however, the view of Easterly, Islam, and Stiglitz (2000) of bank-based systems being more prone to collapse from growth. We do not find any financial system, whether bank based or market based, having a significant negative impact on economic growth for any country group.

VI. Conclusion

The flow of credit and functioning financial markets are essential to support higher levels of economic performance across countries. However, the relationship between financial development and economic growth is complex and requires careful scrutiny in view of the interlinked nature of a multipolar globalized world. This paper takes a closer look at a growth–finance relationship in the era of sustainable development.

We use nonparametric kernel regression methodology to examine how a relationship between indicators of financial development and economic growth varies across country groups (grouped by level of economic development, geographical features, institutional quality, and size of financial systems). We also control for other factors that influence economic growth such as initial GDP per capita, private investment, growth rate of the working-age population, and share of the working-age population with a primary education.

Unlike parametric estimation, nonparametric estimation gives us an estimate of $\partial y/\partial x$, or a partial impact of financial development on economic growth for every country-year observation; parametric methods will give us one estimate. We also get standard errors of each estimate via bootstrapping. We then arrange in ascending order all estimates along with their standard errors to identify the Q1, Q2, and Q3 of estimates of $\partial y/\partial x$ and their corresponding standard errors. This allows us to evaluate the relationship between y and x for various country groups without prespecifying any functional relationship between y and x. We acknowledge that all methods have advantages and limitations. A limitation of our approach is that, unlike Millimet, List, and Stengos (2003), we do not standardize our data to estimate a panel model with country and year effects. Their approach, however, has two limitations. First, they do not deal with endogenous regressors. Second, using standardized data in estimation leads to a scaling issue when compared with nonparametric and semiparametric results. We leave to future works the estimation of a semiparametric model with country and year effects.

We also acknowledge that advanced parametric models can be structured to provide group-varying intercepts and slopes, making their framework more nonparametric adjacent. However, the issue of bias due to functional-form misspecification remains. Parametric models force us to choose between $Y = b_0 + b_1X$ and $Y = b_0 + b_1(X)(Z)$, where $\partial Y/\partial X$ is a constant in the former and a function of Z in the latter. Nonparametric methods utilize local data patterns to estimate the unknown functional relationship between Y and X, or $m(X = x)$. This avoids functional-form misspecification bias. Obtaining an estimate of $\partial Y/\partial X$ at every data point is an added bonus. The approach then is to group these estimates by various criterion, including properties of Z.

Based on our results, progrowth policy makers in all countries will prefer measures of financial development that are bank based to those that are market based. This is particularly applicable to vulnerable country groups such as CSNs including SIDS, LLDCs, HIPCs, and LDCs. Many countries in Asia and the Pacific belong to this subset.

We observe a positive significant impact of financial development on economic growth for all country groups, but only for bank-based measures of financial development. Market-based financial development does not hinder growth, but the impact is not statistically significant either. Our findings caution against the recent trends of vulnerable groups of countries moving resources away from bank-based measures of financial development to market-based measures in the era of sustainable development.

Our paper supports the view that countries with weak institutions will reap more benefits from bank-based financial systems. Likewise, countries with a smaller-than-average banking sector perform better under bank-based financial systems compared with those countries that have a larger-than-average banking sector, indicating the presence of a nonlinear relationship.

Our nonparametric 2SLS estimates not only deal with bias from functional-form misspecification, but also bias from endogenous regressors. Compared with previous studies, we use an updated data set for a larger number of countries. The impact of finance variables on economic performance has enormous policy implications for international institutions, such as the United Nations, that provide policy support to countries in their pursuit of achieving the 2030 Agenda for Sustainable Development.

We only look at how financial development influences economic growth. We leave the examination of a relationship between financial development and inequality for future projects. The role of institutions requires more scrutiny and better data. We leave also that part of the analysis to future works.

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Appendix 1. Parametric Models

$$y_i = \alpha + \beta x_i + \varepsilon_i, \quad i = 1, 2, \ldots, n. \tag{A1.1}$$

Equation (A1.1) describes a linear parametric model, where y_i (or average annual growth rate of GDP per capita) is the dependent variable, x_i is a vector of q regressors, α and β are unknown parameters, and u_i are additive random disturbances ($E(u_i) = 0$). Estimates of α and β are consistent if all regressors included in x_i are uncorrelated with u_i and the functional form is correctly specified.

Appendix 2. Nonparametric Models and Local-Constant Least Squares Estimates

$$y_i = m(x_i) + \varepsilon_i, \quad i = 1, 2, \ldots, n. \tag{A2.1}$$

Nonparametric kernel methods are most effective in dealing with bias caused by functional-form misspecification. Equation (A2.1) represents a typical nonparametric model, where $m(\cdot)$ is a smooth unknown function and remaining variables are same as defined earlier. Here, $m(\cdot)$ is the conditional mean of y given x. In the linear parametric model equation (A1.1) represents, it is assumed that $E(y_i|x_i)$ is $\alpha + \beta x_i$. Only if the true data-generating process is linear, estimates from equation (A1.1) will be consistent; otherwise, they will be biased from functional-form misspecification.

Rather than using ordinary least squares, we can estimate the unknown function $m(\cdot)$ in equation (A2.1) by method of LCLS, giving us the estimate in equation (A2.2):

$$\hat{m}(x) = \frac{\sum_{i=1}^{n} y_i \prod_{s=1}^{q} K\left(\left(x_{si} - x_s\right)/h_s\right)}{\sum_{i=1}^{n} \prod_{s=1}^{q} K\left(\left(x_{si} - x_s\right)/h_s\right)}. \tag{A2.2}$$

Readers can refer to Pagan and Ullah (1999) for a description of the LCLS estimate in equation (A2.2), where $\prod_{s=1}^{q} K((x_{si} - x_s)/h_s)$ is a product kernel and h_s is the smoothing parameter (bandwidth) for the regressor x_s. For every ith observation, the LCLS estimate of the regression function $m(\cdot)$, is simply a weighted average of the dependent variable, where the weights depend on the nearness or farness of every other observation to the window around the ith observation. Details about this window, bandwidth, or smoothing parameter follow in Appendix 3.

Appendix 3. Bandwidth Selection and Irrelevant Regressors

According to Härdle (1990), nonparametric estimates do not depend on the choice of kernel functions; however, the choice of bandwidths is very important as they control the amount by which data are smoothed. Large bandwidths will lead to over-smoothing, resulting in low variance but high bias in the nonparametric estimates. Similarly, small bandwidths will result in high variance but low bias. A popular solution in the nonparametric literature is to determine an optimal bandwidth by minimizing a cross-validation function (where $\hat{m}_{-j}$ is the leave-one-out estimator of $m(\cdot)$) as seen in equation (A3.1):

$$CV(h) = \frac{1}{N}\sum_{i=1}^{N}[y_j - \hat{m}_{-j}(x_j)]^2. \tag{A3.1}$$

Henderson, Papageorgiou, and Parmeter (2013) highly recommend the bandwidth selection procedure be used as opposed to a rule-of-thumb selection, particularly in the case of discrete data, where no rule-of-thumb selection procedure exists. In fact, they insist with a large number of regressors, the cross-validation technique be used and not ocular or rule-of-thumb measures. In addition to being a smoothing parameter, bandwidths also provide information on how each regressor affects a left-hand-side variable. Hall, Li, and Racine (2007) discuss how the cross-validation technique chooses optimal bandwidths such that irrelevant variables have no impact on the prediction of the left-hand-side variable. A regressor is irrelevant when its bandwidth hits an upper bound, which for practical purposes is two times the corresponding regressor's standard deviation. Irrelevant regressors are potential instruments for endogenous variables in the model.

Appendix 4. Nonparametric Models and Local-Constant Least Squares Estimates

An alternative nonparametric regressor estimator, very similar to the LCLS estimator is the LLLS estimator, which instead of fitting a constant locally fits a line locally. To do so, we take a first-order Taylor expansion of the model in equation (A2.1) with respect to continuous regressor x^c:

$$y_i = m(x_j) + (x_i^c - x_j^c)\beta(x_j^c) + \varepsilon_i. \tag{A4.1}$$

In equation (A4.1), $\beta(x^c)$ is the partial derivative of $m(x_j)$ with respect to x^c, that is an estimate of the relationship between the continuous regressor and the left-hand-side variable, estimated at every data point. The LLLS estimator of $\delta(x_j) \equiv [m(x_j)\beta(x_j^c)]'$ is

$$\hat{\delta}(x) = [X'K(x)X]^{-1}[X'K(x)y]. \tag{A4.2}$$

In equation (A4.2), $X = [1\,(x_i^c - x_j^c)]$ and $K(x)$ is a $n \times n$ diagonal matrix of kernel weight functions. The intuition behind this estimation process is that it looks at a window (here the optimal bandwidth) around every observation x and uses the kernel weight function to reweigh all remaining observations in the data set (giving high weights to observations close to the window and low weights to observations far from the window). The LLLS estimator fits a line through x based on all reweighted observations and x. A nice computational feature of this method is that it provides an estimate of β (or the relationship between the regressor and y) for every data point. We use these estimates to obtain an average estimate of the relationship of interest for various subgroups.

As optimal bandwidth on a continuous regressor for the LLLS estimator becomes large, it tends to cover all observations in the data set, thus giving equal weights to all, resulting in nonparametric estimates tending toward estimates from the linear parametric model. If the true model is linear in a regressor, the cross-validation process selects large values of h for that regressor; likewise, this procedure will select small values of h for those regressors that enter the model nonlinearly. For practical purposes, Li and Racine (2004) suggest that a large bandwidth is considered large if it is more than two standard deviations of the regressor. Linearity in a particular regressor, however, does not mean we should switch to a semiparametric model, for there could be important interactions between the linear regressor and remaining regressors, which only a nonparametric model can capture.

Appendix 5. List of Tables

Table A5.1. **Bandwidths for Model (1) and Model (2)**

	Model (1)			Model (2)	
	Upper Bound	Bandwidth		Upper Bound	Bandwidth
Bank	0.8	0.1	*Stock*	3.1	2.6
Y_0	2.1	0.5	Y_0	1.9	0.3
Popgr	3.4	0.8	*Popgr*	3.6	4.9
Inv	1.2	0.3	*Inv*	0.9	0.1
Edu	1.7	0.8	*Edu*	1.7	0.8
PrivY	2.1	1.8×10^6	*PrivY*	1.7	3.7×10^6
Depth	2.0	3.1×10^5	*Depth*	1.8	0.8
Other	1.9	0.8	*Other*	nil	nil

Notes: For both models, the dependent variable is *ecogr*. The upper bound for a given regressor = 2 × standard deviation of that variable.
Source: Authors' calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).

Table A5.2. **Nonparametric Two-Stage Least Squares Estimates for the First, Second, and Third Quartiles**

	Model (1)				Model (2)		
	Q1	Q2	Q3		Q1	Q2	Q3
Bank	0.18***	0.21***	0.23***	*Stock*	0.01	0.03	0.05
	(0.03)	(0.04)	(0.04)		(0.07)	(0.07)	(0.07)
Y_0	–0.07***	–0.06***	–0.05***	Y_0	–0.00***	–0.00***	–0.00***
	(0.02)	(0.02)	(0.02)		(0.00)	(0.00)	(0.00)
Popgr	0.00***	0.00***	0.00***	*Popgr*	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Inv	0.17***	0.21***	0.21***	*Inv*	0.04	0.06*	0.07**
	(0.06)	(0.06)	(0.06)		(0.04)	(0.05)	(0.04)
Edu	0.07*	0.09**	0.1***	*Edu*	–0.04	–0.02	–0.00
	(0.05)	(0.04)	(0.04)		(0.07)	(0.07)	(0.08)
Obs in sample		480		Obs in sample		480	
Obs in estimation		1,155		Obs in estimation		507	

Obs = observations, Q = quartile.
Notes: Dependent variable is *ecogr*. Bootstrap standard errors are in parentheses below each estimate; Reps = 199; ***, **, * indicate estimates are statistically significant at the 1%, 5%, and 10% levels, respectively.
Source: Authors' calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).

Table A5.3. **Median Nonparametric Two-Stage Least Squares Estimates by Geography**

	All Countries	**OECD Countries**	**LLDCs**	**SIDS**
	Model (1)			
$\frac{\partial ecogr}{\partial Bank}$	0.21***	0.18***	0.26***	0.21***
	(0.04)	(0.03)	(0.04)	(0.04)
Obs in subset	480	223	39	23
Obs in estimation	1,155	1,155	1,155	1,155
	Model (2)			
$\frac{\partial ecogr}{\partial Stock}$	0.03	0.04	0.02	0.01
	(0.07)	(0.06)	(0.08)	(0.08)
Obs in subset	480	223	39	23
Obs in estimation	507	507	507	507

LLDCs = landlocked developing countries, Obs = observations, OECD = Organisation for Economic Co-operation and Development, SIDS = small island developing states.
Notes: Bootstrap standard errors are in parentheses below each estimate; Reps = 199; *** indicates estimates are statistically significant at the 1% level.
Source: Authors' calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).

Table A5.4. **Median Nonparametric Two-Stage Least Squares Estimates by Level of Development**

	All Countries	**LDCs**	**CSNs**	**HIPCs**
	Model (1)			
$\frac{\partial ecogr}{\partial Bank}$	0.21***	0.26***	0.24***	0.29***
	(0.04)	(0.05)	(0.04)	(0.06)
Obs in subset	480	18	68	24
Obs in estimation	1,155	1,155	1,155	1,155
	Model (2)			
$\frac{\partial ecogr}{\partial Stock}$	0.03	0.01	0.02	0.02
	(0.07)	(0.07)	(0.07)	(0.08)
Obs in subset	480	18	68	24
Obs in estimation	507	507	507	507

CSNs = countries with special needs, HIPCs = heavily indebted poor countries, LDCs = least developed countries, Obs = observations.
Notes: Bootstrap standard errors are in parentheses below each estimate; Reps = 199; *** indicates estimates are statistically significant at the 1% level.
Source: Authors' calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).

Table A5.5. **Median Nonparametric Two-Stage Least Squares Estimates by Quality of Institutions**

	High IQI		Low IQI	
	$\frac{\partial ecogr}{\partial Bank}$	$\frac{\partial ecogr}{\partial Stock}$	$\frac{\partial ecogr}{\partial Bank}$	$\frac{\partial ecogr}{\partial Stock}$
	0.19***	0.04	0.23***	0.02
	(0.04)	(0.06)	(0.04)	(0.07)
Obs in subset	267	267	124	124
Obs in estimation	1,155	1,155	507	507

IQI = index of institutional quality, Obs = observations.
Notes: Bootstrap standard errors are in parentheses below each estimate; Reps = 199; *** indicates estimates are statistically significant at the 1% level. High IQI ⇒ index is higher than average and institutions are strong; Low IQI ⇒ index is lower than average and institutions are weak.
Source: Authors' calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).

Table A5.6. **Median Nonparametric Two-Stage Least Squares Estimates by Size of Sector**

	Financial Sector Size				
	Larger than Average			Smaller than Average	
	$\frac{\partial ecogr}{\partial Bank}$	$\frac{\partial ecogr}{\partial Stock}$		$\frac{\partial ecogr}{\partial Bank}$	$\frac{\partial ecogr}{\partial Stock}$
	0.19***	0.05		0.23***	0.02
	(0.04)	(0.06)		(0.04)	(0.07)
Obs in subset	240	240	Obs in subset	240	240
Obs in estimation	1,155	1,155	Obs in estimation	507	507

Obs = observations.
Notes: Bootstrap standard errors are in parentheses below each estimate; Reps = 199; *** indicates estimates are statistically significant at the 1% level.
Source: Authors' calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).

Table A5.7. **Descriptive Statistics**

	Observations	Min	Max	Range	Mean	SD	CV
				Model (1) Variables			
ecogr	1,155	–24.6	30.6	55.2	2.1	4.6	2.2
Bank	1,155	–3.5	0.0	3.5	–0.3	0.4	–1.5
Y_0	1,155	–7.7	–0.9	6.8	–4.7	1.1	–0.2
Popgr	1,155	–2.6	21.8	24.4	2.0	1.7	0.8
Inv	1,155	–6.4	–0.5	5.9	–1.7	0.6	–0.3
Edu	1,155	–6.1	–0.3	5.9	–1.9	0.8	–0.4
PrivY	1,155	–9.0	1.8	10.8	–1.5	1.1	–0.7
Stability	1,155	–2.5	2.0	4.6	–0.1	0.5	–4.7
Depth	1,155	–8.2	1.9	10.1	–1.2	1.0	–0.8
Other	1,155	–8.1	1.4	9.5	–1.4	1.0	–0.7
				Model (2) Variables			
ecogr	507	–12.5	15.0	27.4	2.4	3.7	1.6
Stock	507	–8.9	1.8	10.7	–1.8	1.6	–0.9
Y_0	507	–6.4	–2.0	4.4	–4.0	1.0	–0.2
Popgr	507	–1.3	20.8	22.1	1.6	1.8	1.1
Inv	507	–6.4	–0.5	6.0	–1.5	0.4	–0.3
Edu	507	–6.1	–0.7	5.5	–2.0	0.8	–0.4
PrivY	507	–8.3	0.8	9.0	–0.9	0.9	–1.0

CV = coefficient of variation, Max = maximum, Min = minimum, SD = standard deviation.
Note: All variables except *ecogr* and *Popgr* are in log form.
Source: Authors' calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).

Table A5.8. **Country Subsets and Variable Means**

Countries	Bank	Real GDP per Capita	IQI	Stock
Organisation for Economic Co-operation and Development				
Australia, Austria, Belgium, Canada, Chile, Colombia, Czech Republic, Denmark, Estonia, Finland, France, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, the Republic of Korea, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Türkiye, the United States	93.4	35.7	2.2	63.2
SIDS				
Bahrain, Barbados, Belize, Dominican Republic, Fiji, Haiti, Jamaica, Maldives, Mauritius, Trinidad and Tobago	79.4	13.4	1.3	4.1
LLDCs				
Armenia, Bolivia, Botswana, Burundi, Central African Republic, Kazakhstan, the Kyrgyz Republic, the Lao People's Democratic Republic, Lesotho, Malawi, Mali, Mongolia, Nepal, Niger, Paraguay, Rwanda, Swaziland, Tajikistan, Uganda, Zambia, Zimbabwe	71.3	4.4	1.0	21.3
LDCs				
Bangladesh, Benin, Burundi, Cambodia, Central African Republic, Democratic Republic of the Congo, Gambia, Haiti, the Lao People's Democratic Republic, Lesotho, Liberia, Malawi, Mali, Mauritania, Mozambique, Myanmar,[a] Nepal, Niger, Rwanda, Senegal, Sierra Leone, Sudan, Tanzania, Togo, Uganda, Yemen, Zambia	66.4	2.7	0.8	6.9
HIPCs				
Benin, Bolivia, Burundi, Cameroon, Central African Republic, Cote d'Ivoire, Democratic Republic of the Congo, Gambia, Ghana, Haiti, Honduras, Liberia, Malawi, Mali, Mauritania, Mozambique, Nicaragua, Niger, Rwanda, Senegal, Sierra Leone, Sudan, Tanzania, Togo, Uganda, Zambia	65.2	3.5	0.9	4.0

GDP = gross domestic product, HIPCs = heavily indebted poor countries, IQI = index of institutional quality, LDCs = least developed countries, LLDCs = landlocked developing countries, SIDS = small island developing states.

Notes: Countries with special needs are either LDCs, LLDCs, or SIDS. We remove Singapore from country subsets SIDS and CSN. Real GDP per capita is measured in 1,000 United States 2011 dollars. [a]Effective 1 February 2021, ADB placed a temporary hold on sovereign project disbursements and new contracts in Myanmar.

Source: Authors' calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).

Table A5.9. **List of Country Subsets and Time Periods Considered in Recent Literature**

Authors	Sample Countries	Type of Data	Sample Period
King and Levine (1993)	77 developed and developing countries	Panel	1960–1989
Levine and Zervos (1998)	42 developed and developing countries	Panel	1976–1993
Deidda and Fattouh (2002)	119 developed and developing countries	Panel	1960–1989
Rioja and Valev (2004)	74 developed and developing countries	Panel data	1961–1995 (5-year averages)
Shen and Lee (2006)	48 developed and developing countries	Pooled panel Pooled panel	1976–2001
Ergungor (2008)	46 developed and developing countries	Cross-section Cross-section	1980–1995
Law and Singh (2014)	87 developed and developing countries	Panel	1980–2010 (5-year averages)
Henderson, Papageorgiou, and Parmeter (2013)	101 developed and developing countries	Panel	1960–2000 (5-year averages)
This paper	98 developed countries, LDCs, CSNs, HIPCs, LLDCs, and SIDS	Pooled panel	1960–2015

CSNs = countries with special needs, HIPCs = heavily indebted poor countries, LDCs = least developed countries, LLDCs = landlocked developing countries, SIDS = small island developing states.
Source: Authors' calculations based on data from the World Bank's World Development Indicators (accessed 15 October 2019) and Feenstra, Inklaar, and Timmer (2015).