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Does Economic Diversification Lead to Financial Development? Evidence From Topography

Abstract

An influential theoretical literature has observed that economic diversification can reduce risk and increase financial development. But causality operates in both directions. A well functioning financial system can enable a society to invest in more productive but risky projects, thereby determining the degree of economic diversification. Thus, OLS estimates of the impact of economic diversification on financial development are likely to be biased. Motivated by the economic geography literature, this paper uses instruments derived from topographical characteristics to estimate the impact of economic diversification on the development of finance. The IV estimates suggest a large and robust role for diversification in shaping financial development

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JEL Codes: O14;G21

[1] I am grateful to Thorsten Beck, Simon Johnson, Arvind Subramanian and Thierry Tressel for helpful discussions. Naomi Griffin and Zhaogang Qiao provided excellent research assistance. All remaining errors are mine.

I. INTRODUCTION

Greater diversification in economic production can reduce risk, engendering financial development. In the last decade, an influential theoretical literature has formalized this structural explanation of financial development (Acemoglu and Zilbotti [1997], Saint-Paul [1992], Greenwood and Jovanovic [1990]). A common theme among these models is that causality operates in both directions. The diversification of risk across a range of imperfectly correlated sectors—cross section diversification--can benefit the financial system. At the same time, a well developed financial system can allow a society to invest in more productive but risky projects, shaping production patterns and leading to higher levels of economic development. But how big is the impact of cross section diversification on financial development? And how does this production structure explanation compare with those that emphasize institutions and legal traditions?

Apart from historical studies[2], there has been surprisingly little empirical research quantifying the relationship between the pattern of economic production and the development of the financial sector. Moreover, because of the possible feedback from financial development to cross section diversification, OLS estimates of the impact of economic diversification on the level of financial development are likely to be biased. To help evaluate these theoretical approaches to development and finance[3], this paper estimates the impact of economic diversification on various indicators of financial development using the exogenous variation in a country's topography.

Although the use of topographical data is new in economics[4], our approach is firmly motivated by economic theory. Topographical characteristics such as the distribution of the land area by elevation, as well as by bioclimatic (biome) classes are geophysical characteristics not commonly thought to be affected by human activity over the short term. They do however exert a powerful influence on natural endowments and on the cost of moving goods within a country. And well developed theories of comparative advantage, as

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[2] See for example (North and Thomas [1973], Wringley [1988] and Kennedy [1987]).

[3] There is however a large literature that examines the impact of finance on growth, surveyed recently by Levine [2005].

[4] Hoxby [2000] uses rivers and other waterways as an instrument for school district boundaries in the United States. Cutler and Glaeser [1997] use the same variable to study the impact of spatial segregation on the economic outcomes of population groups. Of course, geographical variables, such as distance from the equator and length of coastlines have been used extensively in the empirical growth and trade literatures [Barro and Sala-i-Martin (2003) and Gallup et. al(1998]

well as the more recent theoretical literature in economic geography[5] suggest that these factors can influence production patterns.

In particular, the economic geography literature observes that transportation costs can shape the pattern of economic production in the manufacturing sector. At the same time, a vast literature on road construction documents that the variation in the terrain grade—the rise and fall of the surface area--as well as soil characteristics can exponentially affect the cost of building roadways and rail lines (Aw [1981]; Tsunokawa [1983]); Highway Research Board [1962], Paterson [1987]. Even after construction, the terrain also affects the time and energy required to move goods within a country and the maintenance of transport networks.

Building on these theoretical arguments, the analysis uses the plausibly exogenous variation induced by topography to estimate the impact of manufacturing sector diversification on financial sector development. Both the IV and OLS estimates indicate that greater cross section diversification is associated with increased financial development. But the IV estimates derived from the variation in topography are several times larger, suggesting that the impact of cross section diversification on the financial sector is economically large. For example, the IV point estimates imply that a one standard deviation increase in diversification is associated with about a 0.81 standard deviation increase in the level of credit to the private sector supplied by the banking system.

There is also support for the notion that the general quality of institutions and the protection of property rights can positively affect the level of financial development (Beck et. al [2003]), although the estimated impact of institutions is considerably smaller than cross section diversification. But when conditioned on cross section diversification, there is little evidence that historical differences in legal traditions significantly affect financial development (La Porta et. al [1997]).

Taken together, these results lend support to the large historical and theoretical literature that emphasize a causal relationship between the structure of economic production and the development of the financial system. These results imply that by impeding financial sector development, the concentration of economic activity common in developing countries, can adversely affect development. This paper is organized as follows. Section II discusses the empirical framework and data; Section III presents the main results; Section IV considers various alternative specifications, and Section V concludes.

II. Empirical Framework and Data Overview

An extensive theoretical literature has analyzed the self reinforcing relationship between economic diversification and the development of finance. Thus, our rendition of this

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[5] Standard references include Krugman [1991, 1979]; Krugman and Venables [1995] and Fujita, Krugman and Venables [1999].

interaction is purposely minimal. We develop a highly stylized example to illustrate the main empirical issues involved in estimating the impact of diversification on financial development. Consider an economy with two sectors. One sector contains a single risk free project with return *r*: a government bond for example. The other sector is more productive, but risky. For simplicity, we assume that this more productive but risky sector has just two negatively correlated projects: *A* and *B*. To make the example as stark as possible, we assume that these two projects have identical returns, R, that are perfectly negatively correlated, with $R > r$. More precisely, with probability *p* sector *A* (*B*) returns R (0), while with probability $1 - p$ sector *A* (*B*) returns 0 (R).

To illustrate the impact of the production structure on financial development, suppose both projects *A* and *B* were operational. A risk averse lender would lend only to the productive sector, allocating her capital, W, equally between the two projects. However, with one project operational, an agent with constant relative risk aversion would allocate only $\frac{p}{1+p}$ fraction of her capital to the more productive but risky sector, keeping $\frac{1}{1+p}$ in the low return storage technology. Thus, this simple example illustrates how the degree of cross section diversification can influence the allocation and availability of credit[6].

However, the level of financial development can also determine cross section diversification. To succinctly capture the flavor of these arguments, suppose that opening project B entails a fixed cost F. Suppose further that $F > W$, so that project B could not be opened with the initial capital W. But if the initial investment in A turned out to be successful, then the available loanable funds would be sufficient to open sector B. In particular, with constant relative risk aversion, project B would then be opened with the extra resources if $F < \Phi(W)$, where $\Phi'(W) > 0$. That is, the available pool of loanable funds—the level of financial development— in turn can also shape the pattern of economic production, enabling new projects to be undertaken. And this self reinforcing relationship can render OLS estimates of the impact of diversification on measures of financial development biased.

The estimation framework is based on a cross section of countries. For country i let FID_i denote the level of financial development; DIV_i is a measure of economic diversification; X_i is a vector of other country observables, and ε_i is a residual term; β and the $\alpha_j s$ are parameters to be estimated:

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6 Models that do not explicitly model the formation of financial intermediaries can ignore the role of cross sector diversification [Saint-Paul (1993)]. In this case, increased specialization can lead to more developed financial markets, since specialization concentrates risk, increasing the demand for risk mitigating financial instruments.

$$FID_i = \alpha_0 + X_i\alpha + \beta DIV_i + \varepsilon_i \qquad (0.1)$$

Since FID_i and DIV_i evolve jointly, shocks to FID_i are also likely to influence DIV_i, making the assumption $E\left(\varepsilon_i \middle| DIV_i, X_i\right) = 0$ implausible despite conditioning on a rich vector of country observables. In addition to simultaneity bias, social norms that govern credit use, non-repayment, and general attitudes towards risk; as well as managerial and regulatory competence are all highly persistent unobservables that can shape both the pattern of production and financial development, leading to omitted variable bias. Also, measuring the pattern of production is subject to considerably uncertainty, and measurement error can cause OLS estimates of β to be biased downwards. The confluence of these sources of inconsistency makes it difficult to a priori discern the direction of bias in the OLS estimate of β.

A. Measuring The Structure of Economic Production

Measures of economic diversification are inherently sensitive to the level of aggregation. Consider again the simple example of an economy with two sectors: safe low return and more productive but risky; the more productive sector has two possible projects: A and B. Suppose that only the risky sector was operational, with both projects A and B active. Depending on the level of aggregation, such an economy might be characterized as highly specialized, since economic activity is concentrated in only one sector. However, with production ongoing in two negatively correlated projects, a finer classification method would suggest diversification.

To address issues of aggregation, we use the United Nations Industrial Development Organization (UNIDO, 2003) database, which reports both employment and value added shares only in the manufacturing sector at the 3-digit ISIC code[7]. We use the Gini measure—reserving alternative measures for the robustness section--to summarize the pattern of economic activity across the ISIC codes for each country. Economic activity is measured using both the value added and employment shares in the manufacturing sector. Production in economies with low Gini measures are "smoothly" distributed across a wide range of activities--diversified, while economies with high Gini measures are specialized or concentrated in just a few activities.

[7] Using employment and value added shares as a measure of sectoral concentration is common in the literature. See Imbs and Wacziarg (2003), Krugman (1991) and Sukkoo Kim (1995) for examples. That said, these approaches do not capture the extent to which returns are correlated across sectors, and only imperfectly measure diversification.

B. Topography

To consistently estimate β, we rely on the exogenous cross country variation in topography to instrument diversification in the manufacturing sector, DIV_i. The geospatial data is taken from the Center for International Earth Science Information Network [CIESIN (2001)]. We measure topography using both the distribution of land area by elevation LEV_i, and the distribution of land area by bioclimatic[8] (biome) classes: BIO_i. These are two distinct geophysical characteristics, allowing us to perform various over identification tests. The raw elevation data list the number of square kilometers across 12 elevation levels—ranging from below 5 meters, 5 to 10 meters, 10 to 25 meters and so forth up to above 5000 meters. The distribution of land area by biome classes lists the number of square kilometers across 16 biome categories, extending from tropical and subtropical moist broadleaf forests to rock and ice. To maintain consistency with the existing literature there are 50 countries in the benchmark specification (highlighted in bold in Tables 1 and 2), but 71 countries in more parsimonious specifications.

We summarize the distribution data using the Gini coefficient[9], which measures the concentration of a country's land area among the various categories. Countries with land areas distributed across many elevation categories, but concentrated within a single elevation category, such as plateaus, will have higher Ginis. From Table 1, Belgium--predominantly flat--and Nepal—mostly mountainous—have the smallest degree of land area concentration by elevation. In the case of Belgium most of the land area is relatively equally distributed among the lower elevation categories in Belgium. Nepal has a similarly equal distribution of land, but at higher altitudes.

That is, the Gini coefficient provides information about the shape of the distribution rather than whether a country is mountainous or flat. South Africa and the bordering state of Namibia have the most unequal or concentrated land area distribution. In both cases their land areas span nearly all twelve elevation levels, but is mostly concentrated at higher elevations plateaus: over 60 percent of South Africa's land area is located between 800 and 1500 meters. To help visualize the differences in Ginis across countries, Figure 1 plots the distribution land of area by elevation for South Africa and Belgium. Much of South Africa is dominated by a high elevation plateau, while Belgium's land mass is relatively smoothly distributed at low elevation levels.

[8] Bioclimatic classes or zones are divisions commonly used to classify variation in the habitat of plants and animals—terrestrial ecosystems. The classification system relies on the basic natural elements that influence habitat, including the interaction between climate, soil, and vegetation. A comprehensive discussion of the classification methodology can be found in Olson et. al [2001].

[9] In the robustness section we experiment with a variety of alternative distribution statistics.

Examining the distribution of land area across biome classes, Table 2 indicates that about 9 percent of the sample have Gini coefficients of zero--a homogenous distribution of land area by biome classes. All of Kuwait's land area for example is defined as desert and shrub lands, while Korea's is wholly categorized as "temperate broadleaf and mixed forests". At the other extreme, Pakistan has the most unequal distribution of land area across the biome categories; while a significant percentage of the country's land area is located in mountain grasslands and conifer forests, nearly 90 percent of the land area is classified as desert and generic shrub lands.

According to models of geography (Fujita, Krugman and Venables [1999]), transportation costs can affect the pattern of production. These models typically assume that manufacturing requires a fixed cost. And when transportation costs are sufficiently low, manufacturers can concentrate their production geographically so as to realize economies of scale. But increased geographic concentration expands the labor force within the region. This creates a larger market, attracts more manufacturers and makes it profitable to incur the manufacturing fixed cost, leading to a wider variety of goods in the manufacturing sector (backward linkages). In this way, transportation costs can shape the pattern of production within the manufacturing sector.

However, obvious measures of domestic transport costs such as the unit cost of shipping or the tonnage transported on roadways reflect policy choices and income levels and are likely to be endogenous. Instead, a substantial engineering literature has long observed that topographical characteristics such as terrain variability and soil conditions can affect transportation costs. For example, the evidence from road building indicates that the area of site clearance per unit road length, as well as the volume of earthwork—factors that figure prominently in the overall cost of road construction--are *exponentially* related to the variation in the terrain grade—the sum of ground rise plus fall in terrain elevation. Moreover, for the same horizontal distance, moving goods across variable terrain requires both more energy and time[10]. And since these costs are eventually embedded into freight charges, natural terrain variation can induce differences in the transportation infrastructure across countries.

That said, the direction of the impact of terrain variability on transport costs is an empirical question. Intuitively, large elevation Ginis—land area concentrated at one altitude—might indicate low transport costs, since surface transport networks traverse little elevation changes. But populations may cluster to reduce transport costs in countries with land areas equally distributed across several elevation levels—low elevation Ginis. Indonesia for example has one of the most varied land areas by elevation. Yet in part a response to this extreme terrain variability, nearly half of the population lives on the island of Java. Likewise,

[10] See for example (AASHTO (1972); Aw [1981]; Tsunokawa [1983]); Highway Research Board [1962], World Bank [1987] and the references contained therein.

Trinidad and Tobago also has substantial elevation variation, but most of the population lives on the relatively flat north west flood plain.

To help infer the direction of the impact of topography on transport costs, Table 4 examines the link between the Gini measure of terrain grade concentration (LEV_i) and the number of millions of tons of goods transported per kilometer of roadway for a cross section of 62 countries with available data, over the period 1990-2000. A one percent increase in LEV_i is associated with a 2.5 percent increase in the tonnage of goods moved per kilometer. Consistent with the engineering literature, the concentration of the land area at a given elevation, which often entails a smoother more uniform surface either because of high elevation plateaus or low lying plains, can positively affect the volume of goods transported on roads.

To gauge the robustness of this relationship, column 3 controls for population size, as well as per capita income. The LEV_i coefficient is slightly higher, but more precisely estimated. Figure 2 illustrates the conditional correlation between LEV_i and road tonnage, indicating that the linear positive relationship may only be an approximation. Column 4 restricts the sample, excluding those countries that do not appear in the subsequent analyses. Because of missing data this leaves only 30 countries in the specification, but the magnitude of the LEV_i estimate is little changed. While Figure 2 and Table 4 are descriptive, they do illustrate the basic intuition in the more rigorous engineering literature that emphasizes a connection between topographical characteristics, road construction and transport costs.

III. Main Results

A. First Stage

This subsection documents the conditional correlation between the distribution of land area across terrain grade, LEV_i, biome classes, BIO_i and the pattern of production DIV_i in the base specification. To reduce the risk of including potentially endogenous regressors, we establish our main results within a relatively parsimonious framework. The core specification notes that although LEV_i and BIO_i are geophysical features largely exogenous with respect to human activity, they can more generally impact demographic variables. For example, topographical characteristics can affect population density or urbanization—variables which in turn might affect financial development[11]. Thus, the core

[11] For example, greater urbanization might affect the monitoring cost of banks, or the value of real estate, with the latter affecting the balance sheet of banks. That said, these forces accumulate over decades, and are unlikely to invalidate our instrumental variables approach.

specification, a cross-section of 50 countries with data averaged from 1990-2000, includes population density, urbanization and the log of total population, and assumes that conditioned on these variables, LEV_i and BIO_i are uncorrelated with the unobserved determinants of financial development. The robustness section tests this identification assumption. It also considers various permutations of the core specification, including alternative sub-samples, regressors, and years.

Table 5 presents the first stage results for the base specification using manufacturing employment shares (3 digit ISIC: DIV_EM_i) and manufacturing value added (3 digit ISIC: DIV_VA_i) as our two measures of economic diversification. Column 2, which reports the results with DIV_VA_i as the dependant variable, indicates that both LEV_i and BIO_i are individually (p-values=0.04 and 0.00, respectively) and jointly significant (p-value=0.00), with an F-statistic of 8.20 and a partial correlation of 0.21. LEV_i enters with a negative sign. A one standard deviation increase in LEV_i is associated with about a 0.24 standard deviation decrease in DIV_VA_i -- greater concentration of the land area by elevation is associated with more diverse manufacturing sectors.

That is, when the terrain varies across many elevations, but is concentrated at a particular elevation level—a high Gini coefficient—populations may cluster at that elevation level to reduce transport costs. Clustering in turn can lead to a larger market size and an increased variety of products in the manufacturing sector. Figure 3 plots the conditional correlation between the two variables, indicating that the OLS estimate in Table 5 is not driven by influential observations. To further gauge the sensitivity of this relationship to influential observations, column 4 estimates the conditional median, producing estimates of similar precision and magnitude to those obtained using OLS from column 2.

Column 2 of Table 5 also indicates that the concentration of land area by biome classes (BIO_i) is positively associated with increased concentration in the manufacturing sector (DIV_VA_i). A one standard deviation increase in BIO_i is associated with a 0.46 standard deviation increase in DIV_VA_i. This positive relationship in part reflects the link between natural endowments and the pattern of economic production[12]. Indonesia for example has the second most unequal distribution of land area, with about 92 percent of its surface area classified as tropical and subtropical broad leaf forest. At the same time, paper and pulp processing related industries account for a large share of the manufacturing sector. Plotting the conditional correlation between the two variables (Figure 3), as well as estimating the conditional median (column 4) indicate that this relationship is not driven by influential observations. Quantitatively similar results are obtained when using the

[12] Harrigan and Zakrajsec (2000) provide more direct evidence on the link between endowments and production patterns.

employment based measure of diversification DIV_EM_i (columns 3 and 5, and Figures 4 and 5).

We emphasize however that while the direction of the correlations are consistent with some predictions from the economic geography literature, they are not formal tests. In investigating the determinants of diversification, the first stage specification offers no alternative hypothesis. Moreover, because of congestion costs and other factors, multiple equilibria figures prominently in the theoretical literature—a feature not captured by the linear specifications in Table 5[13]. Nevertheless, the correlations in Table 5 provide a plausible source of exogenous variation to consistently estimate equation (0.1).

But despite the plausible exogeneity of these topographical characteristics, the first stage correlation may generate only weak identification. In this case, two stage least squares estimates can be biased towards OLS, and inference can be unreliable.[14] Based on the definition proposed by Stock and Yogo (2001) that a 5 percent hypothesis test rejects no more than 15 percent of the time, the critical value for the weak instrument test based on the first stage F-statistic is 11.59. Thus, to address the challenges posed by these potentially weak instruments, we report results using both the 2SLS and limited information maximum likelihood estimators (LIML), since the latter is known to have better small sample properties and more robust to weak instruments (Mackinnon and Davidson [1993] and the survey by Stock et. al [2002]). Although developed under the maintained assumption of homoscedasticity, we also perform inference on the endogenous variable based on the conditional likelihood ratio test suggested by Moreira (2003).

B. Second Stage: The Impact of Economic Diversification on Financial Development

Using the core specification for a cross section of 50 countries with data averaged over the period 1990-2000, this subsection examines the impact of manufacturing sector diversification on various indicators of financial development. Measures of the willingness

[13] That said, functional form misspecification in the first stage does not affect the consistency of our second stage results [Kelejian (1971)]. See Davis and Weinstein (1996) for formal attempts at evaluating the theoretical predictions in the economic geography literature.

[14] Moreover, weak instruments can magnify even small deviations from our identification assumption. To see this point clearly, we treat topographical instruments as a scalar $\left(TOP_i\right)$, and let $\mathbf{cov}\left(.,.\right)$ denote the covariance between two variables, then the IV estimate of β is $p\,\mathbf{lim}\,\hat{\beta} = \beta + \frac{\mathbf{cov}\left(TOP_i, \varepsilon_{it}\right)}{\mathbf{cov}\left(TOP_i, DIV_{it}\right)}$. Therefore, even a small correlation between our topographical instruments and shocks to financial development can lead to large biases in the IV estimator if DIV_{it} is weakly correlated with TOP_i. See Bound et, al [1995].

and ability of the financial system to supply credit are often imperfect, and we use a variety of common indicators of financial development. Table 6 uses credit issued by deposit money banks to the private sector as a share of GDP $\left(PCD\_GDP_i\right)$ as the dependant variable. PCD_GDP_i conveys the extent to which savings are channeled to investors—as opposed to the public sector.

Columns 2-4 use the value added measure of diversification (DIV_VA_i), reporting results using the two instrumental variables estimators: Limited Information Maximum Likelihood (LIML) and Two Stage Least Squares (2SLS), as well as OLS. All three estimators imply a negative relationship between PCD_GDP_i and DIV_VA_i . But the two IV estimates are very similar, and about 2.4 times larger than the OLS coefficient. From the LIML estimate, a one standard deviation increase in DIV_VA_i is associated with a 0.95 standard deviation decrease in PCD_GDP_i: increased concentration in the manufacturing sector can have an economically large negative impact on the level of financial development. Estimates based on the employment shares measure of diversification (DIV_EM_i) (Columns 5-7) are about 50 percent larger than those in Columns 2-4, and follow a similar pattern: the IV coefficients are nearly identical, but much larger than the OLS estimate.

Although it does not distinguish between claims of deposit money banks on the private or public sector, Table 7 uses claims on the domestic real non financial sector by deposit money banks as a share of central bank assets (DMB_CB_i) as another common indicator of overall financial development [(King and Levine [1993]; Beck, Levine and Loayza [1998])]. From columns 2-4, DIV_VA_i is also negatively associated with DMB_CB_i ; both the LIML and 2SLS estimates are similar, and remain considerably larger in absolute value than the OLS coefficient-- about twice as large in this case. Moreover, the economic impact of DIV_VA_i is substantial; from column 2, a one standard deviation increase is associated with a 0.75 standard deviation decrease in DMB_CB_i . And as with PCD_GDP_i , the estimates are also robust when using the employment based measure of diversification, and are about 50 percent larger that those obtained from DIV_VA_i .

The IV estimates in the baseline specification suggest that economic diversification can have a large impact on indicators of financial development. The analysis now incorporates alternative explanations of financial development, both to assess the robustness of our identification assumption, as well as to compare the impact of diversification relative to these other explanations. In particular, an influential empirical literature has suggested that differences in legal systems can help explain cross country differences in financial sector development [La Porta et. al (1998)]. Legal systems vary in their apportioning of rights between creditors and debtors, and this literature argues that systems that make it costly to enforce debt contracts can raise the cost of credit, influence ownership concentration and also the pattern of economic production [Jensen and Meckling (1976)].

In addition to the legal infrastructure, recent arguments have observed that the security of property rights, and the quality of the more general institutions that govern economic transactions can also shape both the development of finance and the real sector. According to this literature, climate and geography can shape a country colonial experience, determining the post colonial political system and the overall institutions that govern the interaction between individuals and the state—fundamental factors that seem to affect long run economic (Acemoglu et. al [2001]) and financial development [Beck, et.al (2002)].

To incorporate these two explanations into our base specification, we differentiate between the two most widespread legal traditions, using an indicator variable that equals one if a country's legal origin is English and zero otherwise, and a similarly defined indicator variable for French legal origin[15]. To capture more general notions of institutional quality, we also include an index that measures how well the government protects private property. Directly conditioning on these institutional and historical variables reduces the possibility that our topographical instruments might affect financial development through these institutional and legal channels. Also, while our topographical instruments are conceptually distinct from the geographic variables associated with long run institutions, we directly include those geographic variables common in the trade and growth literature as an additional check on our identification assumption. Specifically, we include a country's latitude—the absolute value of latitude, scaled to lie between zero and one; as well as whether a country is landlocked—as summarized by an indicator variable.

Table 8 considers the impact of diversification on the level of credit to the private sector $\left(PCD\_GDP_i\right)$ within this augmented specification. All three estimators continue to suggest a large and negative relationship between DIV_VA_i and PCD_GDP_i . And the IV coefficients remain about 3 times larger than the OLS estimate, although the estimates in Table 8 are generally about 20 percent smaller than the core specification in Table 6. Among the geographic and institutional variables, only the index of state protection of private property rights is significantly related to PCD_GDP_i (p-value=0.01). And a one standard deviation increase in the property rights index is associated with a 0.41 standard deviation increase PCD_GDP_i--an impact that while sizeable, is considerably smaller than the impact associated with diversification. To gauge the effects of co linearity on the precision of the

[15] Supposedly, British Common Law evolved to protect property rights from royal seizure, while the French civil code was designed to consolidate State power [North and Weingast (1989)]. And the law and finance theory allege that legal systems derived from the French civil code provide less legal protection for private property, impeding financial sector development. See Levine (2005b) for a discussion of these issues.

geographic and institutional estimates, column 8 drops the private property rights index from the specification; the results are nearly unchanged compared with column 2.

Table 9 uses a similar approach to study the impact of diversification on claims on the domestic real non financial sector by deposit money banks as a share of central bank assets $\left(DMB\_CB_i\right)$. As with PCD_GDP_i, the IV estimates continue to suggest a large role for diversification in shaping financial depth, and are slightly smaller than those in the core specification (Table 7). For example, the LIML estimate in column 2 implies that a one standard deviation increase in DIV_VA_i is associated with a 0.68 standard deviation decrease in DMB_CB_i -- the implied impact using DIV_EM_i is about 27 percent larger. Also, the impact of diversification continues to be much larger than the various institutional and geographic variables, most of which are not significant. Thus, the impact of economic diversification on financial development remains robust and large after controlling for alternative determinants of financial development and plausible alternative channels through which our instruments might influence financial development.

IV. Sensitivity Analyses

A. Further Endogeneity Tests

Compared to OLS, the IV estimates derived from the variation in topography suggest a large role for economic diversification in shaping financial development. And our identification assumption has not been refuted by the standard omnibus over identification tests. But these tests often have limited power to detect invalid instruments, and since economic theory does not provide a complete list of the causal determinants of financial development, the validity of our IV approach, while plausible, is fundamentally unknowable. Nevertheless, to further assess the plausibility, this subsection considers whether our biome measure of topography might be endogenous.

Economic and demographic pressures can lead to deforestation, and desertification, fundamentally changing ecological systems. The biome measure of topography might reflect these demographic and social forces. At the same time these forces might be closely linked to financial and economic development, making the biome variable potentially endogenous. In contrast, the distribution of land area by elevation is more likely to be exogenous to human activity, especially when considered over a decade[16]. Thus, we use a Hausman test based on this difference in the plausibility of our two instruments.

[16] Of course, economic forces may lead to coastal infills, but these projects typically add only a few square kilometers of land area, and do not systematically alter the distribution of land area by elevation, especially within a decade.

The underlying logic behind this approach is that we have more a priori confidence in the exogeneity of the elevation based instrument LEV_i than in the biome instrument-- BIO_i . Thus, estimates using only LEV_i are likely to be consistent but inefficient. Under the null hypothesis, using both BIO_i and LEV_i are likely to lead to more efficient estimates. Significant differences between the two approaches would cast doubt on the validity of BIO_i . The test is distributed as χ^2 with one degree of freedom. To implement this test we are forced to use only the employment shares measure of diversification, since LEV_i is not significant in the first stage regression with DIV_VA_i as the dependant variable. From Table 10, estimates using only LEV_i are clearly less efficient, and there is little difference in the point estimates between the estimation strategies in Tables 7 and 8: we cannot reject the null that BIO_i is exogenous.

B. Predetermined Regressors

The topographic instruments for diversification appear plausible, but the IV estimates can still be inconsistent if shocks to financial development over the 1990s also influenced the other regressors. While the extent of this inconsistency is likely to be limited given how slowly demographic variables evolve, Table 11 nevertheless uses lagged values of the regressors. Specifically, Table 11 estimates the base specification using the diversification and financial development measures observed in the 1990s, but the average values of urbanization, population density and population levels are observed from 1970-1979. Lagging the demographic regressors by at least a decade reduces the potential for biased estimates due to the possible correlation between shocks to financial development observed over the 1990s and the various demographic variables also observed over the 1990s. For parsimony, Table 11 presents the LIML results using the valued added measure of diversification—the 2SLS are nearly identical, while the OLS results are smaller in magnitude; these results are available upon request.

From Columns 2 and 3, the estimated impact of diversification on the two measures of financial development are nearly identical to those obtained earlier (Tables 6 and 7). Moreover, the coefficients using the lagged demographic variables are also quite similar to those derived using the averaged values over the 1990s. As a further robustness check, columns 4 and 5 also include per capita income averaged from 1970-1979. Per capita income is closely related to the level of financial development, and using lagged values reduce the potential for biased estimates. But despite the potential endogeneity of income, its inclusion helps in gauging whether by directly affecting income levels, the topographical instruments influence financial development beyond their impact on diversification. From columns 4 and 5 of Table 11, the diversification coefficients in the PCD_GDP_i and DMB_CB_i specifications are respectively 30 and 3 percent smaller than the estimates in Tables 6 and 7—differences that lie within sampling error.

C. Alternative Distribution Measures

Measures of concentration can be sensitive to the shape of the underlying distribution, and ignoring inter group inequality can generate biased Gini coefficients in grouped data [Lerman and Yitzhaki (2002)). To assess the sensitivity of the results to the Gini concentration measure, we use two well known additional methods to summarize the distribution data on land area by elevation, biome classes, and economic activity in the manufacturing sector: the Theil Index, and the mean log deviation. These results are reported in Tables 12 and 13, where for brevity, we show only the LIML estimates. These alternative measures of diversification produce results that are quantitatively very similar to those obtained using the Gini metric. In the case of claims on the domestic real non financial sector by deposit money banks as a share of central bank assets $\left(DMB\_CB_i\right)$ for example, one standard deviation increases in the Theil Index and the mean log deviation imply respectively a 0.69 and 0.67 standard deviation declines in DMB_CB_i.

While the preceding measures of concentration are useful in summarizing the distribution of data grouped into qualitative categories—biomes or industry codes—these measures may not fully capture variation among quantitative groups like land elevation. Thus, we also compute the weighted variance of a country's elevation. For each of the 12 elevation categories, we select the midpoint e_i as the relevant elevation level within category i[17]; likewise, let a_i denote the number of square kilometers of land area in category i, so that the country's total land area is given by $A = \sum_{i=1}^{12} a_i$. Then the mean weighted elevation level, m, is given by $m = \frac{1}{A}\sum_{i=1}^{12} a_i e_i$. And the variance of the land area around the mean elevation level is given by $\sum_{i=1}^{12} \frac{a_i}{A}\left(e_i - m\right)^2$, where each category's deviation from the mean elevation level is weighted by that category's share of land area. Thus, higher variances indicate a greater dispersion in the land area from it's mean elevation level[18].

Columns 4 and 7 of Tables 12 and 13 combines this approach to measuring elevation variation with the mean log deviation measures for economic diversification and biome classes. Despite the slightly weaker first stage correlation between the diversification

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[17] For example, we assume that the elevation of the land in the 5-10 meters category is at 7.5 meters. However, since there is no upper bound, elevation levels in the 5000 meters and above category are set at 5000 meters.

[18] The Gini measure of concentration is highly negatively correlated (-0.54) with this weighted variance metric.

measures and the elevation variance, the estimated impact of diversification—both value added and employment measures--on PCD_GDP_i (Table 12) are little changed. However, in the case of DMB_CB_i, the point estimates are smaller and less precisely estimated than those obtained when the variation in elevation is summarized using the mean log deviation.

D. Alternative Samples and Years

Using the base specification, Columns 2 and 3 of Table 14 present results for only the 31 developing countries in the sample. From column 2, the estimated impact of DIV_VA_i on PCD_GDP_i is nearly identical to the overall sample, but not significant at conventional levels (p-value=0.17). Column 3 uses DMB_CB_i as the dependant variable. In this case the DIV_VA_i coefficient is about 25 percent larger than the overall sample, and statistically significant (p-value=0.02). By excluding the institutional and historical variables, the core specification allows for a larger sample of countries, increasing the sample size by about 42 percent. For this larger sample, column 4 of Table 14 indicates that the impact of DIV_VA_i on PCD_GDP_i is robust (p-value=0.06) and remains very similar in magnitude to the point estimate in Table 6. However, examining the impact of DIV_VA_i on DMB_CB_i reveals that while the point estimate is again similar to the overall sample, it is not significant (p-value=0.18).

As a further robustness exercise, Columns 6 and 7 considers the base specification, but with data averaged from 1980-1989. The resulting cross section consists of 49 countries. The diversification point estimates are robust and little changed compared with the 1990s estimates in Tables 6 and 7, as well as with the various sub-samples in columns 2-5. These results suggest that the impact of diversification on financial development is relatively stable across various sub samples, although the precision of the IV estimates can be sensitive to the sample.

E. Other Indicators of Financial Development

By shaping the risk profile of lending portfolios, diversification may also affect the ability of the banking system to attract savings, and supply credit. Table 15 investigates this idea, estimating the impact of diversification on the level of demand, time and savings deposits in deposit money banks, as a share of GDP $\left(DEP\_GDP_i\right)$. For economy of exposition, we only present the LIML estimates. As with the other indicators of financial development, the impact of diversification is economically large: column 2 indicates that a one standard deviation increase in DIV_VA_i is associated with a 0.71 standard deviation increase in DEP_GDP_i, with the DIV_EM_i estimate about 18 percent larger (column 3). As a further robustness check, Table 14 again considers the impact of diversification on claims on the domestic real non financial sector by deposit money banks, but deflated by the overall size of the economy—GDP $\left(DMB\_GDP_i\right)$, instead of central bank assets (Table 7).

The results are stable across specifications, as a one standard deviation increase in DIV_VA_i implies a 0.77 standard deviation increase in DMB_GDP_i.

V. Discussion

Building on the idea that development involves finance as well as goods, a large and influential theoretical literature has explored the causal connections between financial intermediation, the pattern of production and economic development. An empirical literature, of perhaps similar volume, has investigated one side of this channel, documenting a large and robust impact of financial development on economic growth. There is however considerably less empirical evidence on the link between the pattern of production and financial development. Using the exogenous variation in topographical characteristics, this paper has presented instrumental variables estimates suggesting that the production structure can have a robust and economically large impact on financial development.

Across a range of specifications, estimators and measures, economies that have more concentrated manufacturing sectors typically have lower levels of deposits in money banks, deposit money bank assets relative to central bank assets, and lower levels of credit provided by deposit money banks to the private sector. Moreover, while there is little evidence that differences in legal traditions systematically explain cross country variation in financial development, institutional quality does seem to have an impact. These results lend support to the idea found in the development and finance literature that the concentration of economic activity into just a few sectors can hinder financial and overall economic development. When our results are interpreted in this context, they help to understand why many developing countries often remain specialized in exploiting their natural resource endowments, with their financial sectors mainly subsisting on safe government bonds. Whether or not our estimates are large enough to generate multiple equilibria and development traps—a common result in the theoretical literature—is a question left for future research.

While the various specifications, methodologies and endogeneity tests suggest that our instrumental variables approach is plausible, the capacity of economic theory to impose robust exclusion restrictions is limited. And we view the consistency of our results with caution. For example, country borders are not randomly distributed but reflect a complex interplay between political and economic factors, as well as changing military technologies. Over time, these forces may not only determine the geophysical characteristics of national political boundaries, but plausibly the production patterns and the level of financial development within those boundaries. This can potentially bias IV estimates based on topography in directions that are unclear. Therefore, while our approach is the first attempt to estimate the impact of the real sector on finance, future research that is able to exploit other plausible exogenous variation in the pattern of production would help in understanding the links between development and finance.

Table 1. The Distribution of Land Area (000 km^2) by Elevation (in Meters).

Country	Gini Coefficient	<5 M	5M-10 M	10 M-25 M	25M-50M	50M-100M	100M-200M	200M-400M	400M-800M	800M-1500 M	1500 M-3000 M	3000 M-5000 M	>5000 M
Belgium	0.1817	3119	1463	3915	3785	4044	4689	6474	3420	0	0	0	0
Nepal	0.27052	0	0	0	0	8947	12195	9098	14948	25659	33510	29983	12948
Philippines	0.30338	17551	8001	23487	30864	46436	43726	52889	49534	29595	4710	0	0
Denmark	0.31308	9206	4108	10216	13292	7184	602	0	0	0	0	0	0
Indonesia	0.31789	274016	57922	111714	136836	279608	316366	256314	250228	185832	78441	7894	0
Costa Rica	0.32365	1721	817	2108	6280	7528	5915	6130	8109	7506	5743	172	0
Trinidad and Tobago	0.38458	409	258	430	946	1721	710	387	151	0	0	0	0
Sri Lanka	0.39146	5334	2516	6087	7700	14389	17357	6194	3958	2732	946	0	0
Panama	0.40539	4839	1699	3441	7205	14475	13099	13851	10259	5635	1914	22	0
Sierra Leone	0.4105	3334	2000	3506	6302	17250	11593	13529	14884	409	0	0	0
Italy	0.41969	11916	6065	14152	15550	24433	36801	61428	66848	44329	22971	581	0
Korea, Republic of	0.42333	5119	2624	6625	7592	12625	18433	24046	17873	4087	22	0	0
Malaysia	0.42415	23788	6173	14411	25272	60030	68439	53792	52824	25423	5205	65	0
Venezuela	0.42424	41984	7980	21057	48114	161398	156236	104530	178777	134276	60718	2581	0
Tunisia	0.42495	3871	1979	12238	12539	18131	30047	44845	25939	5549	0	0	0
Kuwait	0.42981	1097	602	882	1355	3785	6775	2818	0	0	0	0	0
Argentina	0.43136	34005	24068	75301	149934	431241	481485	482195	414142	349553	151289	186219	8797
Pakistan	0.43314	17443	14475	30563	38113	79516	155871	77946	114854	147762	99153	20842	2108
Cyprus	0.43406	366	108	473	538	1118	1699	1936	1936	667	43	0	0
Austria	0.44233	0	0	0	0	172	4646	14798	24670	22347	17271	258	0
Greece	0.44238	6087	1463	4001	6065	9958	17658	24864	34822	24218	3742	0	0
Chile	0.44479	27660	4151	11034	16518	30262	82334	102315	105262	150859	118360	114381	3506

Japan	0.44732	16863	9184	20153	23810	36844	55986	80893	86098	40930	7270	22	0
New Zealand	0.45338	6840	2646	8474	12561	21809	36629	57040	66826	47964	8410	0	0
Swaziland	0.46086	0	0	0	0	108	903	5721	5313	5463	86	0	0
Thailand	0.46517	19465	10647	22154	35682	52609	148751	105197	85302	37704	1161	0	0
Bolivia	0.46808	0	0	0	0	3269	303375	297374	91281	66482	88614	237086	3420
China (without Taiwan)	0.47142	108958	80756	185189	269182	320261	529944	765373	1182571	2333211	1183932	1804295	606018
United Kingdom	0.47824	12195	4044	11485	21680	71343	62503	39575	19874	667	0	0	0
Honduras	0.4786	5033	1656	3269	4259	6496	8625	13335	30413	34413	5700	0	0
Ghana	0.481	0	0	0	1334	43812	106229	84226	4861	0	0	0	0
Jamaica	0.48374	430	301	796	667	882	1377	2710	3463	452	43	0	0
Fiji	0.48397	2151	301	796	1463	2022	5506	4323	2000	215	65	0	0
Mongolia	0.48419	0	0	0	0	0	0	0	89173	856245	602060	17121	0
Mauritius	0.49604	0	0	43	108	86	839	559	215	0	0	0	0
India	0.49854	63299	43232	88872	137954	287544	509123	850201	802432	161441	102293	149741	88937
United States of America	0.50715	215793	100702	244033	315957	552118	1006000	2022550	1709260	1743070	1488220	58804	22
Mexico	0.51067	55943	32241	72311	88421	97519	125673	159269	212330	407174	626816	5162	0
El Salvador	0.52096	774	344	366	1247	1269	2430	4366	7442	2301	215	0	0
Brazil	0.52134	168582	50179	124361	419713	1595550	1402680	2172530	2020740	580659	4904	0	0
Sweden	0.52587	7098	4624	16239	32714	46200	76268	133222	106337	23939	473	0	0
Portugal	0.52747	1721	1118	2151	4151	9743	20583	25530	21207	6409	86	0	0
Ecuador	0.52903	4388	1097	2947	5786	10776	26692	80721	26240	27703	43963	28197	237
France	0.53197	10432	4216	14368	27574	74204	150601	133889	71580	44501	16217	452	0
Uruguay	0.53653	5356	3656	11270	22885	49276	68052	17207	22	0	0	0	0
Iceland	0.54497	2000	1334	3312	3699	6087	8087	17938	40436	16798	2000	0	0
Colombia	0.54609	14884	6474	23896	34736	179616	330690	231494	90206	83388	121694	31768	22
Peru	0.55046	5829	1226	3011	4861	68590	311827	195747	150881	109004	142751	299826	7657
Norway	0.56329	6883	1161	5893	6603	15873	32865	68138	102186	78398	5205	0	6883
Cote d'Ivoire	0.57126	0	0	0	22	30778	63019	180928	48007	710	0	0	0
Kenya	0.57995	2603	1075	3635	7786	21186	54674	104874	172583	121974	93927	2215	0
Senegal	0.58266	6517	6646	30456	82269	54782	17142	989	43	0	0	0	0
Egypt	0.60075	34005	11959	23423	25444	48007	224934	386547	204802	29036	860	0	0
Canada	0.617	214696	62955	165549	268682	491637	1515880	3214970	2438280	1106940	394871	2000	43
Australia	0.62232	111951	52867	100014	201038	811981	1537730	2826310	1945640	131093	688	0	0
Gabon	0.62419	9206	1721	4323	7463	17142	30370	66332	126490	3613	0	0	0
Netherlands	0.63682	203	432	684	2624	538	237	43	0	0	0	0	0

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Malawi	0.63803	0	0	0	538	1549	1828	2818	55642	57707	7872	0	0
Finland	0.64002	2990	2086	10173	16884	68074	146923	81667	5958	495	0	0	0
Zimbabwe	0.64451	0	0	0	0	0	258	15594	97368	271585	7657	0	0
Hungary	0.65184	0	0	22	65	30757	45533	14841	1914	86	0	0	0
Iran (Islamic Republic of)	0.66577	20153	16733	24197	17142	17981	26563	70268	257390	588402	579455	11421	0
Spain	0.66623	4345	2624	4087	6969	14045	28757	79151	187144	164216	18088	65	0

Countries in the core specification sample are in bold. Source: Center for International Earth Science Information Network (2001).

Table 2. The Distribution of Land Area (000 km^2) by Bioclimatic Classes.

Country	Gini Coefficient	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
Mauritius	0	1860	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cyprus	0	0	0	0	0	0	0	0	0	0	0	0	11094	0	0	0	0
Denmark	0	0	0	0	53119.25	0	0	0	0	0	0	0	0	0	0	0	0
Kuwait	0	0	0	0	0	0	0	0	0	0	0	0	0	15614	0	0	0
Korea, Republic of	0	0	0	0	114336	0	0	0	0	0	0	0	0	0	0	0	0
Netherlands	0	0	0	0	38445.99	0	0	0	0	0	0	0	0	0	0	0	0
Belgium	0	0	0	0	30721	0	0	0	0	0	0	0	0	0	0	0	0
Austria	0.0593	0	0	0	36997	46954	0	0	0	0	0	0	0	0	0	0	0
Swaziland	0.12115	3734	0	0	0	0	0	6902	0	0	6797	0	0	0	0	0	0
Fiji	0.17727	9047	4311	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Turkey	0.24706	0	0	0	305864	101290	0	0	107853	0	0	0	262941	0	0	0	0
Nepal	0.24727	26049	0	22550	20388	17452	0	19098	0	0	33134	0	0	0	0	0	9
Italy	0.29026	0	0	0	59161	54671	0	0	0	0	0	0	184607	0	0	0	0
New Zealand	0.29037	0	0	0	141864	0	0	0	53469	0	39557	0	0	0	0	0	0
Portugal	0.30254	0	0	0	17947	0	0	0	0	0	0	0	72943	0	0	0	0
Thailand	0.33582	266461	232085	0	0	0	0	0	0	0	0	0	0	0	10193	0	0
Spain	0.34871	0	0	0	76397	0	0	0	0	0	0	0	428585	0	0	0	0
Cote d'Ivoire	0.35657	149583	0	0	0	0	0	173757	0	0	0	0	0	0	531	0	0
Honduras	0.36607	39080	19250	51118	0	0	0	0	0	0	0	0	0	0	2894	0	0
Sierra Leone	0.37673	47425	0	0	0	0	0	19059	0	0	0	0	0	0	6297	0	0
Greece	0.38525	0	0	0	14683	0	0	0	0	0	0	0	113271	0	0	0	0
United Kingdom	0.40836	0	0	0	215300	21721	0	0	0	0	0	0	0	0	0	0	0
El Salvador	0.43265	1044	8239	10368	0	0	0	0	0	0	0	0	0	0	907	0	0
Bolivia	0.43301	341877	365526	0	0	0	0	131012	0	29555	218201	0	0	0	0	3928	0
Ghana	0.43646	79516	0	0	0	0	0	159143	0	0	0	0	0	0	1750	0	0
Jordan	0.43834	0	0	0	0	0	0	0	11757	0	0	0	9559	68834	0	0	0
Namibia	0.45445	0	0	0	0	0	0	24220	0	10717	0	0	0	57527	0	0	0

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Tunisia	0.45517	0	0	0	0	2568	0	0	0	10842	0	0	78859	60974	0	0	0
Chile	0.45782	0	0	0	304225	0	0	0	29572	0	97739	0	148369	106888	0	0	15
Sri Lanka	0.46868	14804	47225	0	0	0	0	0	0	0	0	0	0	2124	0	0	0
Mongolia	0.47083	0	0	0	0	132144	40578	0	615759	0	82100	0	0	695359	0	0	0
Sweden	0.4711	0	0	0	127881	0	261127	0	0	0	0	52131	0	0	0	5702	0
Philippines	0.47172	243094	0	7076	0	0	0	0	0	0	0	0	0	0	0	0	0
Zimbabwe	0.48168	0	0	0	0	0	0	385242	0	0	7191	0	0	0	0	0	0
Jamaica	0.48949	8148	2151	0	0	0	0	0	0	0	0	0	0	0	338	0	0
Senegal	0.4919	0	0	0	0	0	0	196095	0	0	0	0	0	0	1602	0	0
Norway	0.49776	0	0	0	8492	17295	95155	0	0	0	0	186742	0	0	0	0	0
Hungary	0.49955	0	0	0	92976	42	0	0	0	0	0	0	0	0	0	0	0
Iceland	0.49989	0	0	0	0	0	86970	0	0	0	0	0	0	0	0	0	10
China (without Taiwan)	0.50238	1502387	0	0	2320950	518837	83	0	624287	119132	2440062	0	0	1742830	0	0	46
Gabon	0.52332	214465	0	0	0	0	0	47314	0	0	0	0	0	0	5028	0	0
South Africa	0.52482	29453	0	0	0	0	0	167892	0	0	382378	0	95307	540835	845	0	0
France	0.54047	0	0	0	462031	18660	0	0	0	0	0	0	66202	0	0	0	0
Malawi	0.54615	95	0	0	0	0	0	78214	0	4910	21399	0	0	0	0	23219	0
Japan	0.55379	1511	0	0	277702	53270	0	0	0	0	0	0	0	0	0	0	0
Australia	0.56336	32412	0	0	552367	0	0	2108322	576141	0	11996	0	778542	3562437	0	0	0
Panama	0.56509	65118	4713	0	0	0	0	0	0	0	0	0	0	0	3208	0	0
Canada	0.57186	0	0	0	646046	770129	4572210	0	674742	0	0	2708042	0	0	0	124846	119
Trinidad and Tobago	0.59727	4425	256	0	0	0	0	0	0	0	0	0	0	0	122	0	0
Cameroon	0.59902	244057	0	0	0	0	0	217977	0	497	0	0	0	0	2561	4030	0
Venezuela	0.60067	451837	99934	0	0	0	0	250009	0	6014	3157	0	0	93127	10730	0	0
Egypt	0.61296	0	0	0	0	0	0	0	0	71308	0	0	3653	900886	0	0	0
Malaysia	0.63524	311948	0	0	0	0	0	0	0	0	4339	0	0	0	6540	0	0
Finland	0.63841	0	0	0	4287	0	325556	0	0	0	0	5646	0	0	0	0	0
Iran (Islamic Republic of)	0.64115	0	0	0	399202	63264	0	0	64389	6337	152369	0	0	936614	0	8985	0
Brazil	0.64206	527523	1843	0	0	0	0	21889	0	141716	0	0	0	73408	2581	0	0

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Argentina	0.64569	61432	307932	0	78719	0	0	359372	1578718	114705	283438	0	88	0	0	0	3
Peru	0.65117	868536	48774	0	0	0	0	0	0	0	176553	0	0	183152	267	4088	0
Uruguay	0.65861	0	0	0	0	0	0	173132	1440	337	0	0	0	0	0	0	0
Costa Rica	0.66314	41128	6240	0	0	0	0	0	0	0	0	0	0	0	1047	27	0
Mexico	0.66669	266324	371028	455568	0	1331	0	2445	0	279	302	0	6770	719025	23766	0	0
India	0.66988	1105969	965209	52485	100207	27257	0	15392	0	23379	193024	0	0	733441	13867	0	42
	0.67441																
United States of America	0.67938	12647	6265	16867	2159299	1500984	472823	74712	2414224	19536	0	848802	112662	1603978	187	35153	38
Colombia	0.6841	846797	84353	0	0	0	0	151676	0	0	15510	0	0	26790	8991	0	0
Ecuador	0.6865	194977	25117	0	0	0	0	0	0	2937	15940	0	0	6030	5100	0	0
Kenya	0.7103	76133	0	0	0	0	0	396969	0	73	1702	0	0	96553	2726	10628	0
Zambia	0.71332	0	34807	0	0	0	0	635643	0	81601	1554	0	0	0	0	2114	0
Nigeria	0.74376	126847	0	0	0	0	0	740328	0	5261	13337	0	0	0	17293	4264	0
Indonesia	0.79052	1687529	74395	2760	0	0	0	8913	0	0	10062	0	0	0	40116	0	0
Pakistan	0.81791	0	0	9806	2789	24959	0	0	0	4123	47397	0	0	706581	2455	0	1530

Countries in the core specification sample are in bold. Source: Center for International Earth Science Information Network. Biome Code: A=Tropical and subtropical moist broad leaf forests;B= tropical & subtropical dry broadleaf forests; C= tropical & subtropical coniferous forests; D=temperate broadleaf & mixed forests; E= temperate conifer forests; F= boreal forests/taiga; G= tropical & subtropical grasslands, savannas & shrublands;H= temperate grasslands, savannas & shrublands;I= flooded grasslands & savannas;J= mountain grasslands & shrublands; K= tundra;L= Mediterranean forests, woodlands & scrub;M= deserts & generic shrublands;N= mangroves;O=Lakes;P=Rock and Ice. Source: Center for International Earth Science Information Network (2001)

Figure 1
The Distribution of Land Area Elevation
South Africa and Belgium
(Percent Of Land Area In Each Elevation Level)

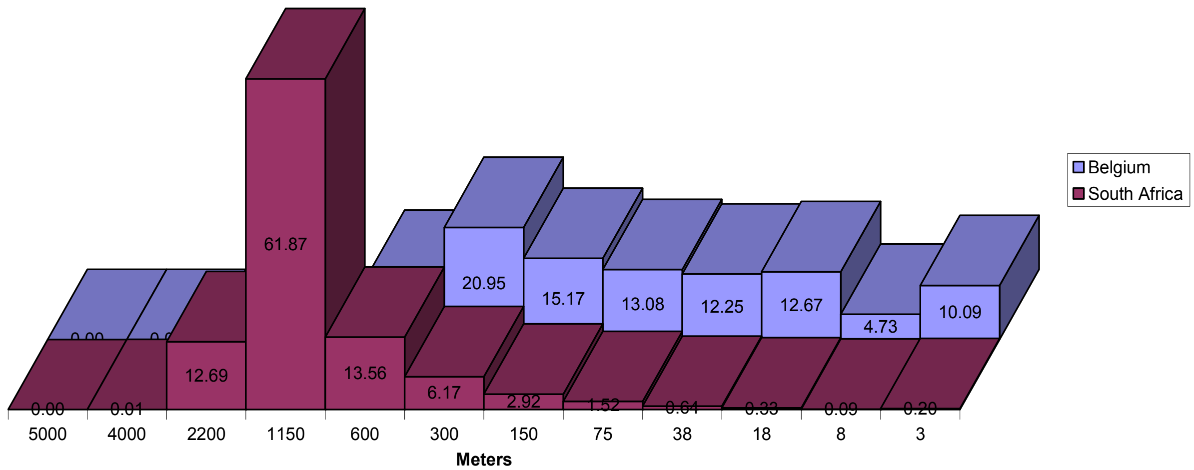


Table 3. Variables, Definitions and Sources

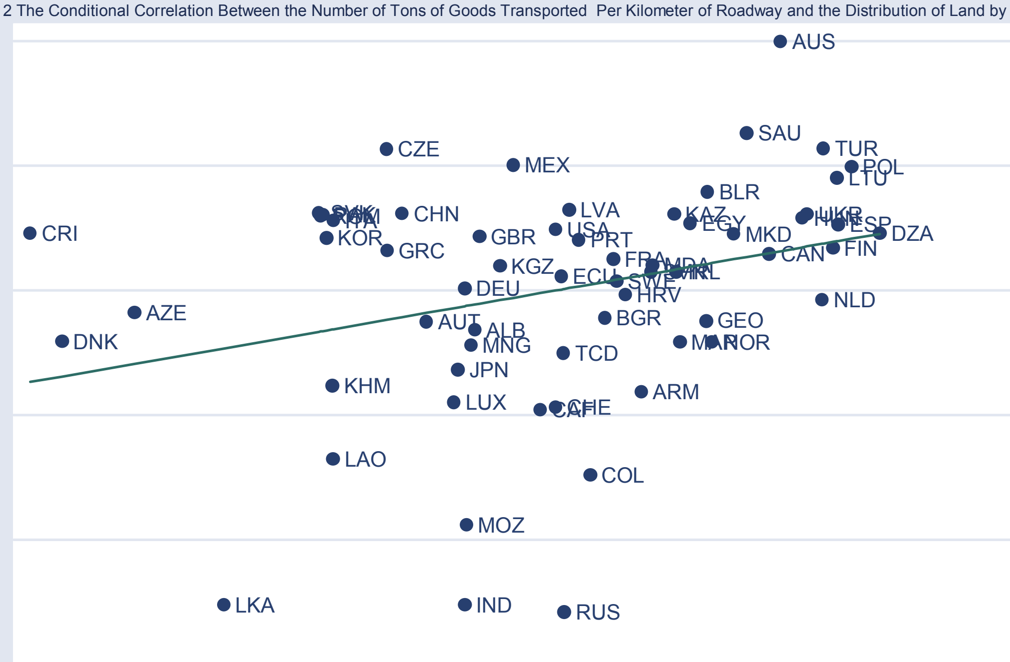
Variable	Definition	Source
Diversification—Value Added and Employment Shares	Gini Coefficient; Mean Log Deviation and Theil Index	United Nations Industrial Development Organization. *Industrial Statistics Database, 3-digit level of ISIC Code*, 2003.
Land Area Distribution, by Elevation and Biome Classes	Gini Coefficient; Mean Log Deviation and Theil Index; Variance.	Center for International Earth Science Information Network, 2001.
Population	Logarithm of Total Population	World Bank, (2003).
Urban Population	Urban Population, as Percent of Total Population	World Bank, (2003)
Population Density	The Number of People per Square Kilometer	World Bank, (2003)
Private Credit by Deposit Money Banks, as a Share of GDP (PCD_GDP)	Total credit issued by deposit money banks to the private sector divided by GDP.	Beck, Demirguc-Kunt and Levine (1999).
Assets in Deposit Money Banks, as a Share of Central Bank Assets (DMB_CB)	Total Assets in Deposit Money Banks Divided by Central Bank Assets	Beck, Demirguc-Kunt and Levine (1999)
Deposits in Money Banks, as a Share of GDP	Demand, Time and Saving Deposits in Deposit Money Banks, Divided by GDP	Beck, Demirguc-Kunt and Levine (1999)
Assets in Deposit Money Banks, as a Share of GDP	Total Assets in Deposit Money Banks Divided by GDP	Beck, Demirguc-Kunt and Levine (1999)
English Law	An indicator variable that equals one if a country's legal origin is primarily English	LaPorta, R., Lopez-de-Silanes, F., Shleifer,A., Vishny, R.W. (1997)
French Law	An indicator variable that equals one if a country's legal origin is primarily French	LaPorta, R., Lopez-de-Silanes, F., Shleifer,A., Vishny, R.W. (1997)
Property Rights	An index measuring the extent to which the government protects private property and enforces laws that protect private property	LaPorta, R., Lopez-de-Silanes, F., Shleifer,A., Vishny, R.W. (1997)
Latitude	The absolute value of the latitude of each country normalized to lie between zero and one	LaPorta, R., Lopez-de-Silanes, F., Shleifer,A., Vishny, R.W. (1999)
Landlocked	An indicator variable that equals one if a country is landlocked	Center for International Earth Science Information Network, 2001.
Road Tonnage	Roads, millions of tons of goods transported per kilometer	World Bank, (2003).

Table 4. The Impact of the Log Gini Measure of Land Area Distribution by Elevation on the Log of the Millions of Tons of Goods Transported per Kilometer of Roadway.

	OLS (2)	OLS (3)	OLS (4)
Log(Gini)	2.462* (1.469)	3.092*** (1.251)	2.820* (1.621)
Log(Population)	---	0.872*** (0.252)	0.817** (0.300)
Per Capita Income	---	0.0009*** (0.001)	0.0001*** (0.00002)
Number of Observations	61	61	30
R-Squared	0.03	0.53	0.48

Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%.

Figure 2 The Conditional Correlation Between the Number of Tons of Goods Transported Per Kilometer of Roadway and the Distribution of Land by Elevation



coef = 3.0920677, (robust) se = 1.2513392, t = 2.47

Table 5. First Stage Results: Base Specification

	Dependant Variable: Manufacturing Sector Diversification—Value Added Based Measure (OLS) (2)	Dependant Variable: Manufacturing Sector Diversification—Employment Based Measure (OLS) (3)	Dependant Variable: Manufacturing Sector Diversification—Value Added Based Measure (Median Regression) (4)	Dependant Variable: Manufacturing Sector Diversification—Employment Based Measure (Median Regression) (5)
Area Biome Classes	0.175***	0.098*	0.203***	0.105
	[0.048]	[0.055]	[0.049]	[0.073]
Area Elevation	-0.178**	-0.172*	-0.252***	-0.268**
	[0.083]	[0.088]	[0.079]	[0.121]
Percent Urban Population	-0.001***	-0.002***	-0.001*	-0.002***
	[0.0003]	[0.0004]	[0.0004]	[0.001]
Population Density	0.0001	0.0002**	0.0002**	0.0002*
	[0.0001]	[0.00009]	[0.0009]	[0.0001]
Log of Population	-0.026***	-0.034***	-0.030***	-0.032***
	[0.006]	[0.008]	[0.006]	[0.009]
Constant	1.042***	1.245***	1.095***	1.260***
	[0.100]	[0.109]	[0.099]	[0.144]
Observations	50	50	50	50
R-squared	0.39	0.59	0.30	
F-Statistic (P-value)	8.20 (0.00)	2.68(0.07)	11.20(0.00)	3.11(0.05)
Partial R-squared	0.212	0.144	--	--
Summary Statistics: Mean	0.549	0.563	0.549	0.563
Summary Statistics: Standard Deviation	0.08	0.084	0.08	0.084

Heteroscedasticity robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. F-Statistic (heteroscedasticity robust) is the joint test that the coefficients of the Area Elevation and Area Biome Classes variables equal zero.

Figure 3. The Conditional Correlation Between Diversfication (Value Added) and the Distribution of Land by Elevation

coef = -.17766424, (robust) se = .08326986, t = -2.13

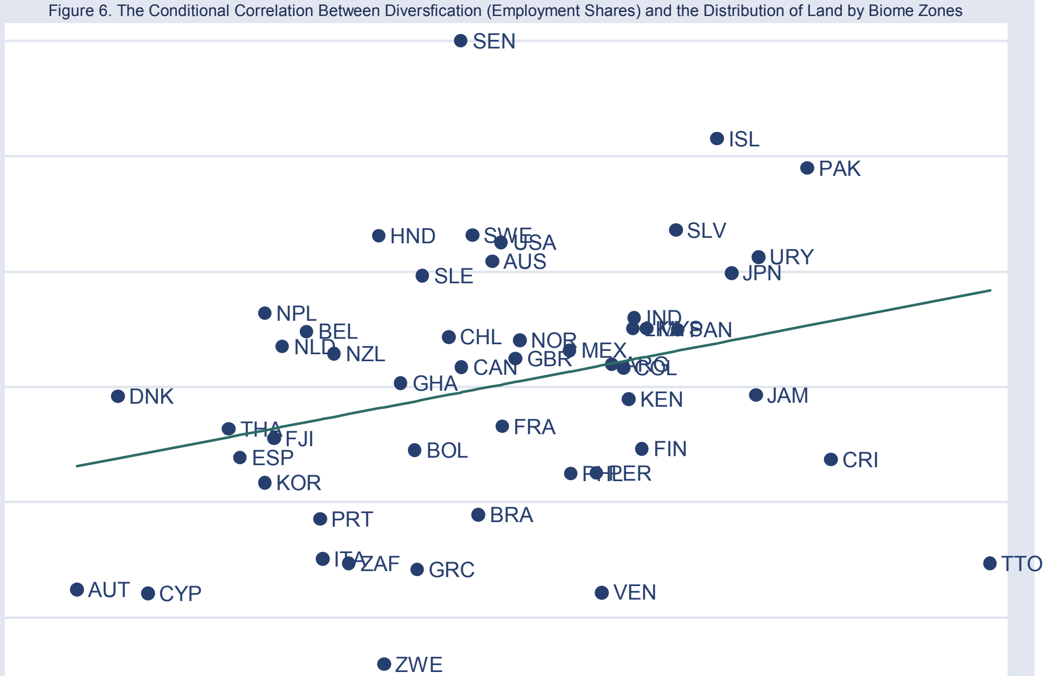
Figure 4. The Conditional Correlation Between Diversfication (Value Added) and the Distribution of Land by Biome Zones

coef = .17512214, (robust) se = .04801791, t = 3.65

Figure 5. The Conditional Correlation Between Diversfication (Employment Shares) and the Distribution of Land by Elevation

coef = -.17220786, (robust) se = .08769184, t = -1.96

Figure 6. The Conditional Correlation Between Diversfication (Employment Shares) and the Distribution of Land by Biome Zones



coef = .09775118, (robust) se = .05530086, t = 1.77

Table 6. The Impact of Diversification—Value Added (DIV_VA_i) and Employment Based (DIV_EM_i) Measures—On The Level Of Private Sector Credit As A Share of GDP—Base Specification.

	LIML (2)	2SLS (3)	OLS (4)	LIML (5)	2SLS (6)	OLS (7)
DIV_VA_i	-3.435***	-3.413***	-1.420***	--	---	---
	[1.092]	[1.080]	[0.429]	---	---	---
DIV_EM_i	--	---	---	-5.056**	-4.960**	-0.697
	---	---	---	[2.462]	[2.384]	[0.557]
Urban Population (Percent)	0.001	0.001	0.004**	-0.004	-0.004	0.004**
	[0.003]	[0.003]	[0.002]	[0.006]	[0.006]	[0.002]
Population Density	0.0005	0.0005	0.0004	0.001**	0.001**	0.001*
	[0.0003]	[0.0003]	[0.0003]	[0.001]	[0.001]	[0.000]
Log of Population	-0.043	-0.043	-0.007	-0.134*	-0.131*	-0.002
	[0.031]	[0.031]	[0.025]	[0.081]	[0.078]	[0.030]
Constant	2.914***	2.894***	1.044*	5.595*	5.483*	0.535
	[1.128]	[1.118]	[0.621]	[2.946]	[2.855]	[0.810]
Observations	50	50	50	50	50	50
R-squared	0.11	0.11	0.33	0.54	0.55	0.24
Over Identification Tests (p-value)	0.115(0.734)	0.12(0.734)	---	0.160(0.689)	0.267(0.605)	---
CLR Test (p-value)	0.003	0.003	---	0.004	0.004	---
Summary Statistics: Mean	0.439	0.439	0.439	0.439	0.439	0.439
Summary Statistics: Standard Deviation	0.295	0.295	0.295	0.295	0.295	0.295

Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%. See Table 3 for Variables' Definition and Sources; Tables 1 and 2 lists the countries in the sample. The Over Identification Test is based on the (heteroscedasticity robust) Hansen J statistic, distributed as Chi-Squared with one degree of freedom. Columns 2 and 5 report the Anderson-Rubin statistic (Chi-Squared with one degree of freedom). Under the weak instrument assumption, the null hypothesis in the CLR Test [conditional likelihood ratio test (Moreira (2003))] is that the diversification point estimate is zero $(\beta = 0)$.

Table 7. The Impact of Diversification—Value Added (DIV_VA_i) and Employment Based (DIV_EM_i) Measures—On The Level of Assets in Deposit Money Banks, As A Share Of Central Bank Assets—Base Specification.

	LIML (2)	2SLS (3)	OLS (4)	LIML (5)	2SLS (6)	OLS (7)
DIV_VA_i	-1.588***	-1.517***	-0.645***	---	---	---
	[0.538]	[0.499]	[0.239]	---	---	---
DIV_EM_i	---	---	---	-2.393**	-2.387**	-0.412
	---	---	---	[1.148]	[1.143]	[0.304]
Urban Population (Percent)	0.002	0.002	0.003**	-0.001	-0.001	0.003**
	[0.002]	[0.002]	[0.001]	[0.003]	[0.003]	[0.001]
Population Density	0.0002**	0.0002**	0.0002**	0.001**	0.001**	0.0002**
	[0.0001]	[0.0001]	[0.000]	[0.0002]	[0.0002]	[0.0001]
Log of Population	-0.020	-0.019	-0.003	-0.064	-0.064	-0.004
	[0.016]	[0.016]	[0.012]	[0.039]	[0.039]	[0.013]
Constant	1.900***	1.834***	1.025***	3.203**	3.197**	0.905**
	[0.589]	[0.556]	[0.304]	[1.405]	[1.399]	[0.370]
Observations	50	50	50	50	50	50
R-squared	0.19	0.21	0.34	0.15	0.15	0.29
Over identification Tests (p-value)	0.805(0.369)	1.789 (0.181)	---	0.021(0.885)	0.03(0.857)	---
CLR Test (p-value)	0.02	0.02	---		0.02	0.02
Summary Statistics: Mean	0.831	0.831	0.831	0.831	0.831	0.831
Summary Statistics: Standard Deviation	0.172	0.172	0.172	0.172	0.172	0.172

Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%. See Table 3 for Variables' Definition and Sources; Tables 1 and 2 lists the countries in the sample. The Over Identification Test is based on the (heteroscedasticity robust) Hansen J statistic, distributed as Chi-Squared with one degree of freedom. Columns 2 and 5 report the Anderson-Rubin statistic (Chi-Squared with one degree of freedom). Under the weak instrument assumption, the null hypothesis in the CLR Test [conditional likelihood ratio test (Moreira (2003))] is that the diversification point estimate is zero $(\beta = 0)$.

Table 8. The Impact of Diversification—Value Added (DIV_VA_i) and Employment Based (DIV_EM_i) Measures—On The Level Of Private Sector Credit As A Share of GDP—Law and Geography Specification.

	LIML (2)	2SLS (3)	OLS (4)	LIML (5)	2SLS (6)	OLS (7)	LIML (8)
DIV_VA_i	-2.797**	-2.725**	-0.954**	---	---	---	-2.462**
	[1.135]	[1.089]	[0.431]	---	---	---	[1.125]
DIV_EM_i	---	---	---	-3.358**	-3.257**	-0.945*	---
	---	---	---	[1.356]	[1.286]	[0.506]	
Percent Urban Population	-0.001	-0.001	0.001	-0.006	-0.006	0.000	0.002
	[0.003]	[0.003]	[0.002]	[0.005]	[0.004]	[0.002]	[0.003]
Population Density	0.0002	0.0002	0.0002	0.001*	0.001*	0.000	0.0004
	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.000]	[0.003]
Log of Population	-0.026	-0.024	0.007	-0.079*	-0.076*	-0.005	-0.0157
	[0.031]	[0.030]	[0.025]	[0.044]	[0.042]	[0.032]	[0.0285]
English Law	-0.097	-0.092	0.028	0.033	0.035	0.076	-0.079
	[0.162]	[0.159]	[0.144]	[0.154]	[0.152]	[0.142]	[0.155]
French Law	-0.114	-0.111	-0.047	-0.033	-0.033	-0.019	-0.166
	[0.141]	[0.139]	[0.138]	[0.148]	[0.146]	[0.140]	[0.141]
Property Rights	0.131***	0.131***	0.127**	0.174***	0.173***	0.139***	---
	[0.049]	[0.048]	[0.051]	[0.051]	[0.050]	[0.050]	---
Latitude	-0.049	-0.038	0.231	0.345	0.346	0.367	0.231
	[0.284]	[0.279]	[0.285]	[0.334]	[0.331]	[0.307]	[0.263]
LandLock	0.091	0.091	0.088	-0.116	-0.110	0.030	0.076
	[0.191]	[0.187]	[0.127]	[0.154]	[0.150]	[0.108]	[0.236]
Constant	2.005	1.935	0.179	3.171**	3.053**	0.342	1.926
	[1.238]	[1.196]	[0.655]	[1.617]	[1.538]	[0.794]	[1.207]
Observations	50	50	50	50	50	50	50
R-squared	0.38	0.39	0.54	0.33	0.34	0.53	0.37
Over identification Tests (p-value)	0.327(0.567)	0.48(0.503)	---	0.338(0.562)	0.396(0.529)	---	0.151(0.697)
First Stage F-Statistic (p-value)	4.48 (0.01)	4.48 (0.01)	---	3.03 (0.06)	3.03 (0.06)	---	4.95 (0.01)
CLR Test (p-value)	0.03	0.03	---	0.04	0.04	---	0.07
Partial R-Squared	0.168	0.168	---	0.161	0.161		0.168

Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%. See Table 3 for Variables' Definition and Sources; Tables 1 and 2 lists the countries in the sample. The Over Identification Test is based on the (heteroscedasticity robust) Hansen J statistic, distributed as Chi-Squared with one degree of freedom. Columns 2 and 5 report the Anderson-Rubin statistic (Chi-Squared with one degree of freedom). The F-Statistic (heteroscedasticity robust) is the joint test that the coefficients on the Area Elevation and Area Biome Distributions measures in the first stage equal zero. Under the weak instrument assumption, the null hypothesis in the CLR Test [conditional likelihood ratio test (Moreira (2003))] is that the diversification point estimate is zero $(\beta = 0)$.

Table 9. The Impact of Diversification—Value Added (DIV_VA_i) and Employment Based (DIV_EM_i) Measures—On The Level of Assets in Deposit Money Banks, As A Share Of Central Bank Assets— Law and Geography Specification.

	LIML (2)	2SLS (3)	OLS (4)	LIML (5)	2SLS (6)	OLS (7)
DIV_VA_i	-1.452*	-1.327**	-0.511*			
	[0.746]	[0.647]	[0.255]			
DIV_EM_i				-1.843***	-1.843***	-0.657**
				[0.693]	[0.693]	[0.280]
Percent Urban Population	-0.0002	-0.0008	0.001	-0.003	-0.003	-0.000
	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]	[0.001]
Population Density	0.00006	0.00003	0.00003	0.0002*	0.0003*	0.000
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.000]
Log of Population	-0.015	-0.013	0.001	-0.046*	-0.046*	-0.010
	[0.019]	[0.017]	[0.012]	[0.024]	[0.024]	[0.015]
English Law	-0.111*	-0.103*	-0.047	-0.045	-0.045	-0.024
	[0.063]	[0.056]	[0.035]	[0.049]	[0.049]	[0.034]
French Law	-0.064	-0.059	-0.030	-0.023	-0.023	-0.016
	[0.065]	[0.061]	[0.050]	[0.059]	[0.059]	[0.049]
Property Rights	0.068**	0.068**	0.066	0.092***	0.092***	0.074*
	[0.033]	[0.033]	[0.039]	[0.031]	[0.031]	[0.038]
Latitude	-0.047	-0.028	0.096	0.156	0.156	0.167
	[0.180]	[0.166]	[0.131]	[0.159]	[0.159]	[0.137]
LandLock	-0.029	-0.030	-0.031	-0.143	-0.143	-0.071
	[0.082]	[0.076]	[0.051]	[0.088]	[0.088]	[0.051]
Constant	1.712**	1.587**	0.778**	2.434***	2.434***	1.042**
	[0.847]	[0.757]	[0.352]	[0.891]	[0.891]	[0.403]
Observations	50	50	50	50	50	50
R-squared	0.35	0.38	0.47	0.33	0.34	0.48
Over identification Tests (p-value)	1.133 (0.287)	2.531 (0.112)	---	0.001(0.989)	0.001(0.989)	---
First Stage F-Statistic (p-value)	4.48 (0.01)	4.48 (0.01)	---	3.03 (0.06)	3.03 (0.06)	---
CLR Test (p-value)	0.09	0.09	---	0.06	0.06	---
Partial R-Squared	0.168	0.168	---	0.161	0.161	

Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%. See Table 3 for Variables' Definition and Sources; Tables 1 and 2 lists the countries in the sample. The Over Identification Test is based on the (heteroscedasticity robust) Hansen J statistic, distributed as Chi-Squared with one degree of freedom. Columns 2 and 5 report the Anderson-Rubin statistic (Chi-Squared with one degree of freedom). The F-Statistic (heteroscedasticity robust) is the joint test that the coefficients on the Area Elevation and Area Biome Distributions measures in the first stage equal zero. Under the weak instrument assumption, the null hypothesis in the CLR Test [conditional likelihood ratio test (Moreira (2003))] is that the diversification point estimate is zero $(\beta = 0)$.

Table 10. Testing The Exogeneity of Area Biome Classes

	Dependant Variable: The Level Of Private Sector Credit, As A Share of GDP (2SLS)	**Dependant Variable: The Level of Assets in Deposit Money Banks, As A Share Of Central Bank Assets (2SLS)**
DIV_EM_i	-2.449*	-1.857**
	[1.458]	[0.944]
Percent Urban Population	-0.004	-0.003
	[0.004]	[0.003]
Population Density	0.0004	0.000
	[0.0003]	[0.000]
Log of Population	-0.051	-0.047
	[0.048]	[0.032]
English Law	0.050	-0.046
	[0.142]	[0.052]
French Law	-0.028	-0.023
	[0.136]	[0.059]
Property Rights	0.161***	0.092***
	[0.051]	[0.035]
Latitude	0.353	0.156
	[0.307]	[0.161]
LandLock	-0.061	-0.144*
	[0.111]	[0.084]
Constant	2.106	2.450**
	[1.709]	[1.138]
Observations	50	50
R-squared	0.33	0.34
Hausman Over identification Test (p-value)	0.02 (0.95)	0.00 (0.99)
First Stage F-Statistic (p-value)	3.57 (0.06)	3.57 (0.06)
Partial R-Squared	0.09	0.09

Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%. See Table 3 for Variables' Definition and Sources; Tables 1 and 2 lists the countries in the sample. The F-Statistic (heteroscedasticity robust) test whether the coefficient on the Area Elevation Distributions measure in the first stage equals zero. The Hausman Over Identification Test is distributed as Chi-Squared with one degree of freedom.

Table 11. Predetermined Regressors

(1)	**Dependant Variable: The Level Of Private Sector Credit, As A Share of GDP (LIML)** (2)	**Dependant Variable: The Level of Assets in Deposit Money Banks, As A Share Of Central Bank Assets (LIML)** (3)	**Dependant Variable: The Level Of Private Sector Credit, As A Share of GDP (LIML)** (4)	**Dependant Variable: The Level of Assets in Deposit Money Banks, As A Share Of Central Bank Assets (LIML)** (5)
DIV_VA_i	-3.293***	-1.584***	-2.325**	-1.253**
	[1.078]	[0.510]	[0.971]	[0.510]
Percent Urban Population	0.002	0.002	-0.002	0.000
	[0.002]	[0.001]	[0.002]	[0.001]
Population Density	0.001*	0.0002**	0.0004*	0.000*
	[0.0004]	[0.0001]	[0.0002]	[0.000]
Log of Population	-0.040	-0.020	-0.024	-0.015
	[0.031]	[0.016]	[0.025]	[0.014]
Per capita Income	---	---	0.000002***	0.000002**
	---	---	[0.00001]	[0.000001]
Constant	2.744**	1.913***	2.023**	1.666***
	[1.081]	[0.535]	[0.932]	[0.523]
Observations	50	50	50	50
R-squared	0.15	0.20	0.43	0.32
Over identification Tests (p-value)	0.19(0.663)	0.81(0.370)	0.486(0.486)	1.14(0.285)
First Stage F-Statistic (p-value)	7.51 (0.002)	7.51 (0.002)	6.59(0.003)	6.59(0.003)
CLR Test (p-value)	0.003	0.03	0.04	0.09

Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%. The dependant variable and DIV_VA_i are averaged from 1990-2000. All other regressors are “initial values” averaged from 1970-1979. See Table 3 for Variables’ Definition and Sources; Tables 1 and 2 lists the countries in the sample. The Over Identification Test is based on the Anderson-Rubin statistic (Chi-Squared with one degree of freedom). The F-Statistic (heteroscedasticity robust) is the joint test that the coefficients on the Area Elevation and Area Biome Distributions measures in the first stage equal zero. Under the weak instrument assumption, the null hypothesis in the CLR Test [conditional likelihood ratio test (Moreira (2003))] is that the diversification point estimate is zero $(\beta = 0)$.

Table 12. The Impact of Diversification—Value Added (DIV_VA_i) and Employment Based (DIV_EM_i) Measures— On The Level Of Private Sector Credit As A Share of GDP—Law and Geography Specification: Alternative Measures of Diversification.

	LIML (Theil Index) (2)	LIML (Mean Log Deviation) (3)	LIML (Mean Log Deviation; Elevation Variance) (4)	LIML (Theil Index) (5)	LIML (Mean Log Deviation) (6)	LIML (Mean Log Deviation; Elevation Variance) (7)
DIV_VA_i	-1.086***	-0.991***	-0.890***		---	---
	[0.349]	[0.338]	[0.285]		---	---
DIV_EM_i	--	--	--	-1.007***	-1.230***	-1.221***
	--	---	--	[0.324]	[0.377]	[0.423]
Percent Urban Population	-0.000	-0.002	-0.001	-0.005	-0.006	-0.006
	[0.003]	[0.003]	[0.003]	[0.004]	[0.004]	[0.004]
Population Density	0.0002	0.00003	0.000	0.0003	0.0002	0.000
	[0.0002]	[0.0002]	[0.0003]	[0.0003]	[0.0002]	[0.0004]
Log of Population	-0.034	-0.049	-0.042	-0.067**	-0.081**	-0.081*
	[0.027]	[0.034]	[0.031]	[0.033]	[0.040]	[0.043]
English Law	-0.064	-0.050	-0.035	0.061	0.008	0.009
	[0.150]	[0.156]	[0.147]	[0.143]	[0.173]	[0.167]
French Law	-0.077	-0.105	-0.096	0.001	-0.062	-0.062
	[0.137]	[0.159]	[0.152]	[0.140]	[0.166]	[0.164]
Property Rights	0.143***	0.107	0.109	0.177***	0.143**	0.143**
	[0.048]	[0.073]	[0.068]	[0.048]	[0.069]	[0.068]
Latitude	-0.045	0.076	0.106	0.261	0.462	0.462
	[0.279]	[0.286]	[0.267]	[0.289]	[0.362]	[0.364]
LandLock	0.128	0.074	0.075	-0.091	-0.119	-0.118
	[0.218]	[0.240]	[0.222]	[0.126]	[0.167]	[0.168]
Constant	1.127	1.661	1.412	1.621*	2.323**	2.298**
	[0.732]	[1.048]	[0.914]	[0.835]	[1.056]	[1.133]
Observations	50	50	50	50	50	50
R-squared	0.33	0.16	0.26	0.43	0.11	0.12
Over identification Tests (p-value)	0.159 (0.690)	0.627 (0.428)	0.012 (0.911)	0.24 (0.624)	0.03 (0.857)	0.05 (0.828)
First Stage F-Statistic (p-value)	7.08 (0.00)	7.13 (0.00)	6.13 (0.00)	5.66 (0.00)	8.41 (0.00)	5.68 (0.00)
CLR Test (p-value)	0.041	0.005	0.008	0.037	0.004	0.009

Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%. See Table 3 for Variables' Definition and Sources; Tables 1 and 2 lists the countries in the sample. The Over Identification Test is based on the Anderson-Rubin statistic (Chi-Squared with one degree of freedom). The F-Statistic (heteroscedasticity robust) is the joint test that the coefficients on the Area Elevation and Area Biome Distributions measures in the first stage equal zero. Columns 4 and 7 summarizes the dispersion of Area Elevation using the weighted variance. Under the weak instrument assumption, the null hypothesis in the CLR Test [conditional likelihood ratio test (Moreira (2003))] is that the diversification point estimate is zero $(\beta = 0)$.

Table 13. The Impact of Diversification—Value Added (DIV_VA_i) and Employment Based (DIV_EM_i) Measures— On Level of Assets in Deposit Money Banks, As A Share Of Central Bank Assets—Law and Geography Specification: Alternative Measures of Diversification.

	LIML (Theil Index) (2)	LIML (Mean Log Deviation) (3)	LIML (Mean Log Deviation; Elevation Variance) (4)	LIML (Theil Index) (5)	LIML (Mean Log Deviation) (6)	LIML (Mean Log Deviation; Elevation Variance) (7)
DIV_VA_i	-0.471	-0.332*	-0.198	---	---	---
	[0.325]	[0.174]	[0.200]	---	---	---
DIV_EM_i	---	---	---	-0.449**	-0.494**	-0.317
	---	---	---	[0.207]	[0.216]	[0.279]
Percent Urban Population	0.0002	0.0001	0.001	-0.002	-0.002	-0.001
	[0.002]	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]
Population Density	-0.0003	0.0004	0.0003	0.0004	0.0004	0.0004
	[0.0004]	[0.0005]	[0.0004]	[0.0004]	[0.0004]	[0.0005]
Log of Population	-0.015	-0.014	-0.004	-0.028	-0.034	-0.017
	[0.020]	[0.015]	[0.018]	[0.019]	[0.022]	[0.026]
English Law	-0.081	-0.061	-0.041	-0.044	-0.029	-0.035
	[0.054]	[0.039]	[0.037]	[0.042]	[0.037]	[0.037]
French Law	-0.039	-0.043	-0.030	-0.030	-0.005	-0.024
	[0.058]	[0.052]	[0.052]	[0.054]	[0.050]	[0.051]
Property Rights	0.072**	0.059*	0.061*	0.071**	0.090***	0.069**
	[0.033]	[0.031]	[0.033]	[0.031]	[0.029]	[0.031]
Latitude	-0.009	0.073	0.113	0.205	0.117	0.196
	[0.181]	[0.126]	[0.119]	[0.140]	[0.132]	[0.131]
LandLock	-0.014	-0.036	-0.034	-0.107	-0.119	-0.085
	[0.078]	[0.070]	[0.052]	[0.073]	[0.078]	[0.077]
Constant	0.000	0.000	0.756	-0.002	-0.002	1.069
	[0.002]	[0.001]	[0.585]	[0.002]	[0.002]	[0.795]
Observations	50	50	50	50	50	50
R-squared	0.39	0.45	0.49	0.40	0.44	0.46
Over identification Tests (p-value)	1.497 (0.221)	1.13 8(0.286)	2.03 (0.18)	0.361 (0.548)	0.31 (0.578)	2.01 (0.17)
First Stage F-Statistic (p-value)	7.08(0.00)	7.13 (0.00)	6.13 (0.00)	8.41 (0.00)	5.66(0.00)	5.68 (0.00)
CLR Test (p-value)	0.189	0.183	0.442	0.101	0.13	0.387

Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%. See Table 3 for Variables' Definition and Sources; Tables 1 and 2 lists the countries in the sample. The Over Identification Test is based on the Anderson-Rubin statistic (Chi-Squared with one degree of freedom). The F-Statistic (heteroscedasticity robust) is the joint test that the coefficients on the Area Elevation and Area Biome Distributions measures in the first stage equal zero. Columns 4 and 7 summarize the dispersion of Area Elevation using the weighted variance. Under the weak instrument assumption, the null hypothesis in the CLR Test [conditional likelihood ratio test (Moreira (2003))] is that the diversification point estimate is zero $(\beta = 0)$.

Table 14. The Impact of Diversification—Value Added (DIV_VA_i) Measure— On Financial Development—Base Specification: Alternative Samples.

	Dependant Variable: The Level Of Private Sector Credit, As A Share of GDP (LIML) (2)	Dependant Variable: The Level of Assets in Deposit Money Banks, As A Share Of Central Bank Assets (LIML) (3)	Dependant Variable: The Level Of Private Sector Credit, As A Share of GDP (LIML) (4)	Dependant Variable: The Level of Assets in Deposit Money Banks, As A Share Of Central Bank Assets (LIML) (5)	Dependant Variable: The Level Of Private Sector Credit, As A Share of GDP (LIML) (6)	Dependant Variable: The Level of Assets in Deposit Money Banks, As A Share Of Central Bank Assets (LIML) (7)
	Developing Countries	*Developing Countries*	*Expanded Sample*	*Expanded Sample*	*1980s*	*1980s*
DIV_VA_i	-3.359	-1.965**	-2.944*	-2.091	-2.666***	-2.035***
	[2.437]	[0.883]	[1.564]	[1.558]	[0.907]	[0.686]
Urban Population (Percent)	-0.003	0.0004	0.003	0.002	-0.0001	0.001
	[0.004]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]
Population Density	-0.00008	0.0002	0.001***	0.0004**	0.0004	0.000
	[0.0003]	[0.0002]	[0.0003]	[0.0001]	[0.0003]	[0.000]
Log of Population	-0.065	-0.022	-0.028	-0.042	-0.024	-0.024
	[0.042]	[0.022]	[0.037]	[0.039]	[0.027]	[0.023]
Constant	3.452	2.219**	2.272	2.532	2.148**	2.181***
	[2.229]	[0.919]	[1.527]	[1.574]	[0.916]	[0.717]
Observations	31	31	71	71	49	49
R-squared	0.47	0.31	0.12	0.14	0.52	0.35
Over identification Tests (p-value)	1.91 (0.167)	0.046 (0.831)	1.542 (0.214)	3.622 (0.57)	0.049 (0.825)	0.125 (0.723)
First Stage F-Statistic (p-value)	2.58 (0.09)	2.58 (0.09)	4.20 (0.01)	4.20 (0.01)	4.95 (0.012)	4.95 (0.012)
CLR Test (p-value)	0.111	0.180	0.051	0.101	0.015	0.034

Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%. See Table 3 for Variables' Definition and Sources; Tables 1 and 2 lists the countries in the sample. The Over Identification Test is based on the Anderson-Rubin statistic (Chi-Squared with one degree of freedom). The F-Statistic (heteroscedasticity robust) is the joint test that the coefficients on the Area Elevation and Area Biome Distributions measures in the first stage equal zero. Under the weak instrument assumption, the null hypothesis in the CLR Test [conditional likelihood ratio test (Moreira (2003))] is that the diversification point estimate is zero $(\beta = 0)$.

Table 15. The Impact of Diversification—Value Added (DIV_VA_i) Measure— and Employment Based (DIV_EM_i) Measures—On Financial Development: Alternative Measures of Financial Development.

	Dependant Variable: The Level of Assets in Deposit Money Banks, As A Share Of GDP (LIML) (2)	**Dependant Variable: The Level of Assets in Deposit Money Banks, As A Share Of GDP (LIML)** (3)	**(Dependant Variable: Deposits in Money Banks, As A Share of GDP (LIML)** (4)	**(Dependant Variable: Deposits in Money Banks, As A Share of GDP (LIML)** (5)
DIV_VA_i	-3.191***	---	-2.101**	---
	[1.211]	---	[0.921]	---
DIV_EM_i	---	-3.770**	---	-2.270*
	---	[1.735]	---	[1.215]
Percent Urban Population	-0.001	-0.007	-0.001	-0.005
	[0.003]	[0.005]	[0.002]	[0.004]
Population Density	0.0004	0.001**	0.0003	0.001*
	[0.0003]	[0.0008]	[0.0003]	[0.0003]
Log of Population	-0.032	-0.092*	-0.036	-0.068*
	[0.033]	[0.055]	[0.027]	[0.041]
English Law	-0.089	0.061	-0.024	0.078
	[0.172]	[0.172]	[0.130]	[0.129]
French Law	-0.054	0.039	-0.038	0.024
	[0.157]	[0.166]	[0.123]	[0.127]
Property Rights	0.135***	0.183***	0.098**	0.127***
	[0.050]	[0.057]	[0.040]	[0.034]
Latitude	0.127	0.576	0.016	0.314
	[0.298]	[0.350]	[0.221]	[0.246]
LandLock	0.141	-0.093	0.105	-0.035
	[0.194]	[0.170]	[0.188]	[0.143]
Constant	2.332*	3.590*	1.851*	2.430
	[1.332]	[2.067]	[1.040]	[1.480]
Observations	50	50	50	50
R-squared	0.46	0.41	0.37	0.39
Over identification Tests (p-value)	0.00 (0.995)	1.45 (0.24)	0.075 (0.78)	1.76 (0.18)
First Stage F-Statistic (p-value)	4.48 (0.02)	3.03 (0.06)	4.48 (0.02)	3.03 (0.06)
CLR Test (p-value)	0.021	0.037	0.069	0.141

Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%. See Table 3 for Variables' Definition and Sources; Tables 1 and 2 lists the countries in the sample. The Over Identification Test is based on the Anderson-Rubin statistic (Chi-Squared with one degree of freedom). The F-Statistic (heteroscedasticity robust) is the joint test that the coefficients on the Area Elevation and Area Biome Distributions measures in the first stage equal zero. Under the weak instrument assumption, the null hypothesis in the CLR Test [conditional likelihood ratio test (Moreira (2003))] is that the diversification point estimate is zero $(\beta = 0)$.

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