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How To Prioritize across Productivity Determinants?

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Abstract[*]

This study is a first contribution to prioritization across productivity determinant capabilities that attempts to obtain the equivalent of a "shadow price" for each of these capabilities by estimating their impact on the success a country may have in reaching higher income per capita groups. The prioritization of these determinants—spanning different sectors—seems to be specific to the income per capita group to which a country belongs. Moreover, empirical estimates reveal that interactions among sectors matter for increasing the probability of climbing up the income-per-capita ladder, reflecting the existence of complementarities across sectors, thus indicating that the joint improvement of some of them may be necessary before effects are noticeable. Results also indicate that the identification of priorities by looking at the impact that sectors have on increasing the likelihood of advancing to a better income per capita group may or may not coincide with the size of sector gaps typically used for the determination of priorities, as larger gaps do not necessarily capture the relevance of sectoral restrictions and their interactions.

JEL Codes: O10, O40, O47
Keywords: Development, Productivity, Per capita income priorities, Growth

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1. Introduction

In a context of ebbing external factor tailwinds, Latin America and other emerging markets are once again engaging in serious introspection on how to attain higher per capita incomes. In particular, the search is now turning towards domestic sources of growth. Given the present growth slowdown, governments are now facing tighter budget constraints, and therefore they must be very selective in how they allocate spending to facilitate private sector growth and attain larger per capita incomes.

Recent research (Pagés, 2010) suggests that much of the gap in income per capita levels between Latin American countries and the United States is not due to a lack of factor accumulation, but rather to a fall in productivity levels vis-à-vis those of the United States. Thus, a key question is how governments can help in increasing productivity by boosting those sectors that influence productivity levels; i.e., should they invest in education, health or infrastructure? And which of those sectors provide the largest return in maximizing the chances of reaching a larger income per capita?

This is a complex question, as the impact that an increase in each of these variables may have on productivity and hence on income per capita may very well depend on the levels of other variables, implying non-linear effects. As discussed in detail by Hausmann, Rodrik and Velasco (2005), binding constraints may affect each other so that the relaxation of one constraint may not necessarily lead to more investment and higher growth as long as some other related constraint still binds.

But even if these nonlinearities could be identified, a second question emerges: how should one determine the relevance of each constraint? This is largely an empirical question, and much about it can be learned from the experiences of countries that were able to address these constraints and reach higher income per capita levels. Of course, there may be unique elements to each of these experiences that are hard to assess. However, there may also be several elements that are shared among these experiences, and these can be captured by empirical models.

A popular strategy to identify priorities for growth is to look into constraints to investment, an approach that became widely known as "growth diagnostics" (see Hausmann, Rodrik and Velasco, 2005). Instead of drawing on a laundry list of sectors and a "wholesale reform" approach, this methodology largely looks for signals indicating whether the problem of lagging investment lies in inadequate returns to investment, inadequate private appropriability of returns, or inadequate access to finance. It provides very well-structured reasoning on how to discard or keep potential constraints in the analysis, serving as an instrument to identify hurdles to investment and growth. However, it does not provide a framework to quantify explicitly the value of the constraints, although it relies on a relevant set of variables to make an informed assessment.

Another popular approach consists of looking into sets of indicators and their gaps relative to some benchmark to determine priorities. This can materialize into rankings across different dimensions, such as the World Economic Forum's Global Competitiveness Report (2014) which, using an executive opinion survey, looks into institutions, policies, and factors that determine the level of productivity of a country and in turn set the level of prosperity that can be reached by an economy.[1] Along the same lines, the World Bank's Doing Business Report (2014) compares countries using a series of measures of business regulations and their enforcement to facilitate firm start-up and growth, with the view that without a dynamic private sector, no economy can provide a good, and sustainable, standard of living.[2] This methodology also provides rankings, as well as distances to the frontier—or best observed performance.

Another approach employing gaps used by the OECD, called "Going for Growth," focuses on gaps in outcome and policy variables across different sectors affecting productivity and participation, and it determines priorities when gaps in a particular sector (both in outcomes and policies) lie below the OECD average (see OECD, 2005). Yet another approach, developed at the IDB (see Borensztein et al., 2014), likewise analyzes development gaps, but the novelty here is that gaps are constructed relative to predicted values consistent with a country's income per capita. Once these gaps are identified, the largest ones are chosen to determine priorities.[3]

While these approaches provide a framework for a systematic analysis and identification of the largest gaps in particular areas of interest and using different benchmarks, they face a potential issue in that the largest gaps may or may not coincide with sectors in which the value of constraints is the largest. For example, a country may rank poorly in terms of institutions, yet it may experience high growth and a faster path to development if the institutional constraint turns out not to be very binding in that particular country. They also differ according to whether they

[1] This report was introduced in 2004.
[2] This report was introduced in 2002.
[3] Predicted values are the fitted values obtained from regressions of each indicator against income per capita levels.

focus on the implicit issues behind growth—such as productivity or development of the private sector—or consider all areas of development.

Although each methodology focuses on a particular set of indicators and potential restrictions, they all share the view that a set of capabilities must be developed for a country to become more productive and grow. This view is in line with Hausmann and Hidalgo (2009), who show that, even after controlling for initial levels of development, their (implicit) measure of capabilities is a useful predictor of future economic growth.[4] Moreover, Hausmann and Hidalgo (2011) argue in a theoretical model that since many products require the combination of several capabilities, countries with few capabilities will have a lower probability of finding alternative uses for any additional capability than countries having a large pool of capabilities, thus leaving countries with low capabilities with little incentive to invest in the accumulation of additional capabilities. This nonlinear view is also shared by Rodrik (2013a), who embeds capabilities in a model in which an economy's long-run level of productivity is determined by its capabilities, and accumulation of such capabilities must be large enough to achieve measurable increases in productivity, given the multidimensional nature of those capabilities and the complementarity among them.[5]

Against this methodological background, and given the relevance for Latin America of focusing more on productivity than factor accumulation (see Pagés, 2010) our approach focuses on productivity determinants and their impact on the likelihood of a country's ability to jump to a larger income-per-capita group.[6] A key contribution of the methodology we use is that, in contrast to existing methodologies, it allows for an implicit valuation of the relevance of each sector by looking into the impact that each sector has on increasing the probability of reaching a larger income per capita group. The impact of each sector is not necessarily associated with the

[4] Daude, Nagengast and Perea (2014) link this implicit measure of capabilities to capability determinants encompassing macroeconomic conditions, financial development, economic structure, external sector, demographics, education and skills, infrastructure and importance of the primary sector. This exercise allows them to provide more specific determinants of these implicit capabilities.

[5] Rodrik introduces the impact of capabilities on the productivity of services and the industrial sector. He also introduces unconditional convergence as another element affecting productivity in the industrial sector, given the empirical evidence provided in Rodrik (2013b) showing the presence of unconditional convergence in organized manufacturing industries at a rate of about 2 percent per year.

[6] Alternatively, we could have measured the impact of productivity determinants on productivity levels. However, productivity measurements are subject to a myriad of issues (problems in capturing capital utilization levels, problems in capturing skill levels, etc.) that make productivity level comparisons across countries and in time difficult at best. For this reason, we stick to comparisons using income per capita levels.

size of the gap in that sector; that impact and the size of the gap of that sector may or may not coincide.

Using a generalized ordered Probit, this methodology learns from countries that have been able to attain larger per capita incomes—or "jumpers"—to identify priority areas. A useful aspect of this methodology is that estimated priorities are specific to each group of countries (classified by per capita incomes), so that sectors may differ in terms of their relevance in increasing the likelihood of jumping to the next income per capita cluster, depending on the group to which a country belongs. Another interesting feature of the empirical model is that the impact of each sector is conditional on the levels attained by a country in other sectors, implicitly capturing the concept of interaction across constraints and the existence of nonlinear effects in the data. Thus additional expenditure to boost education, for example, may depend on health levels. These nonlinear effects are consistent with the literature described above. They are also consistent with critiques to the Washington Consensus of the 1990s, in the sense that countries may have invested in several sectors with meager results in terms of reaching higher levels of per capita income: to the extent that investments were made across the board without properly identifying the largest constraints—and their interactions—many countries achieved results that were less successful than expected, which led to reform fatigue in more than a few cases.

The rest of the paper proceeds as follows. Section 2 describes our empirical strategy, and Section 3 presents the optimal choice of country clusters by income per capita. Section 4 proceeds with the estimation of Priorities for Productivity and Income (or PPIs), and Section 5 describes robustness and goodness of fit. Section 6 provides an application to the case of Peru for illustration purposes. Section 7 concludes.

2. Empirical Strategy

This methodology was designed with Latin American countries in mind, but given the fact that many of them have reached middle income status and aspire to advance to higher income per capita groups, it was necessary to include high income (OECD) countries in the analysis as well. As a matter of fact, some high income countries today were recently middle income countries, so much can be learned from their experiences. Moreover, OECD countries have rich sectoral datasets, yet another reason to include them in the analysis.[7] Thus our sample includes a total of 49 countries—19 from Latin America and the Caribbean, and 30 from the OECD.[8]

Given the non-linearities described above, the empirical framework that best fits these characteristics is an ordered Probit approach, in which countries are clustered into different income-per-capita groups and the likelihood of "jumping" to a higher income group is set to depend on the different factors that affect productivity. Along the lines of the classification used by OECD's "Going for Growth" exercise, we worked with eight categories that can affect productivity: Labor Markets, Education, Health, Infrastructure, Innovation, Integration and Trade, Telecommunications, and Capital Markets.[9] OECD's choice of sectors is based on a stockpile of analytical work that studies the impact that different sectors have on productivity levels.[10] Notice that these sectors constitute a wide array of horizontal policies that governments can carry out to improve productivity.

Each sector encompasses a set of indicators that are representative of developments in each of the eight categories mentioned above. A key issue faced in this study was the considerable lack of sufficiently long time series for indicators at the sectoral level readily available for all countries. Departing from an original set of 83 potential indicators, the sample had to be narrowed down to 34 indicators due to lack of data in both the time series and cross-section dimensions that could be used consistently to produce eight sectoral indicators strictly

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[7] The authors largely benefited from discussions and support from OECD Staff engaged in the "Going for Growth" exercise through the provision of methodological details and associated databases.

[8] Our sample includes 49 countries, 19 from Latin America and the Caribbean (Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay and Venezuela) and 30 from OECD (Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom and United States (Luxembourg and New Zealand were excluded from the sample due to lack of data in some Capital Markets and Labor Markets indicators, respectively). Caribbean countries other than the Dominican Republic and Jamaica were excluded due to the substantial lack of sectoral data. However, the methodology can still be applied for these countries making out of sample predictions.

[9] The last two categories are not included in the "Going for Growth" exercise. However, we considered them important for Latin American countries given that their levels of access to capital markets is much less developed than in OECD countries, where financial depth and integration are much more pronounced. A similar argument applies for telecommunications.

[10] For a general overview, see Bouis, Duval and Murtin (2011). For sectoral papers on links to productivity and growth, see for example, Bassanini and Scarpetta (2001) for the impact of human capital on output per capita growth; Égert, Kozluk and Sutherland (2009) for the effects of infrastructure investment on growth; Janz, Löö and Peters (2004) for the relationship between innovation and productivity; Alcalá and Ciccone (2004) for the effect of trade on productivity; Dahl, Kongsted and Sørensen (2010) for the effect of information and communication technology (ICT) on productivity growth; and Bloom, Canning and Sevilla (2003) for the effects of health on aggregate output.

comparable in time for all 49 countries.[11] As a result, each sector is represented on average by four indicators throughout the period 2000-2012, all of which are listed in Appendix Table A1.[12,13]

3. Optimal Choice of Country Clusters by Income per Capita

The first step of the methodology consists of grouping countries in "income per capita clusters." For this exercise, country-time observations on (the log of) income per capita in constant U.S. dollars (adjusted for purchasing power parity) for the 49 countries in the sample, spanning the period 2000-2012, were subject to clustering analysis. Based on residual sum of squares analysis, an optimal number of clusters can be selected. This approach, also known as the "elbow" method, looks for important reductions in the within group sum of squares as the number of clusters increases. The fact that the within-group sum of squares falls drastically from one to four groups, but little thereafter, leads to the selection of four clusters (see panel (a) of Appendix Figure A1).

Countries are grouped into four clusters using the hierarchical clustering method.[14] Notice that each cluster contains country-year observations spanning the period 2000-2012. Thus, a cluster could contain elements that differ in time but yet are similar in terms of GDP per capita (for example, Peru in 2012 could be clustered together with Argentina in 2000). Appendix Table A2 contains the list of country-year observations for each of the four clusters. For illustration purposes, Figure 1 shows country groupings at three different points in time. Notice that by 2012 Latin American countries belong to clusters 1, 2 and 3. Cluster 1 contains the lowest income per capita countries (Honduras and Nicaragua), while Cluster 2 includes Ecuador, Jamaica, El Salvador, Guatemala and Bolivia. Cluster 3 contains the seven biggest Latin

[11] The list of 83 indicators was constructed on the basis of consultations with each of the IDB's sectoral departments involved on the relevance of indicators to be used, as well as the existence of readily available datasets.

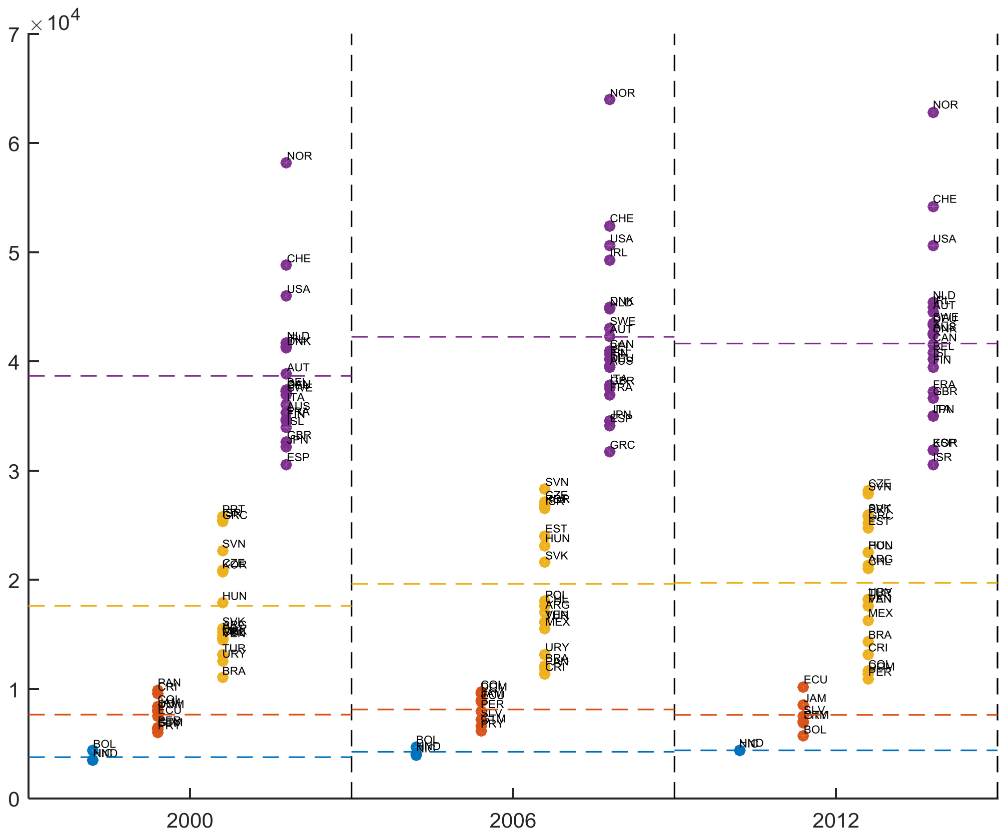
[12] The IDB is currently engaged in the production of indicators on labor informality, innovation, and competition indicators of product market regulation indicators (in association with the World Bank and OECD), that could eventually be used once sufficiently long datasets become available.

[13] These indicators try to capture as well as possible trends in each of the sectors. However, it must be acknowledged that some of the indicators used may have different roles to play at different points in time given technological change. For example, Internet access, which is a relevant indicator in explaining productivity today, may have not been so previously. However, given the relatively short time span in our sample, such technological changes are likely not an issue.

[14] Hierarchical clustering methods have the characteristic that at each step of the algorithm only one object changes group (groups are nested from previous steps). The algorithm starts with as many groups as countries exist in the sample, and in every step distances are first calculated between existing groups, and then the two closest groups are merged. This is done systematically until four groups are obtained.

American economies—Argentina, Brazil, Chile, Colombia, Mexico, Peru and Venezuela—as well as Uruguay, Costa Rica, Panama, and the Dominican Republic. At the upper end of the spectrum, Group 3 also contains some European countries such as Estonia, Czech Republic, Turkey, Poland and Portugal. No Latin American country has yet reached cluster 4, mostly composed of developed countries ranging from Israel to Norway.

Figure 1. Clusters by GDP per Capita (in Constant USD, PPP Adjusted)



Source: IDB, Research Department.

4. Estimation of Productivity Determinant Priorities

With four income per capita clusters at hand, we proceed next with construction of the sectoral indicators. Each of the 34 variables listed in Appendix Table A1 was normalized using all population data—e.g., using information for all 49 countries throughout the period 2000-2012.

Normalized data were then used to construct each of the eight sectoral indicators, which are simple averages of individual indicators.[15]

A first issue that arises for estimation is that of potential endogeneity between per capita incomes and sectoral indicators. For this reason, we used lagged values of indicators in our estimation to reduce potential endogeneity issues. We also conducted (Vector Error Correction) Granger causality tests between income per capita and an aggregate indicator of productivity determinants—defined as the simple average of sectoral indicators—to test whether the data shows time precedence going from the aggregate indicator to income per capita.[16],[17] Results indicate that, while we can reject the hypothesis that the aggregate indicator does not Granger cause income per capita, we cannot reject the hypothesis that income per capita does not Granger cause the aggregate indicator (see Appendix Table A3). While this is no final proof of causality, it does suggest that there is one-sided temporal precedence in that lags of changes in the aggregate sectoral indicator affect current changes in GDP per capita, but not vice versa. This is consistent with the fact that most of the indicators used are structural in that they will not be easily affected by shocks to income, as would be the case for education, where there is little chance that shocks to current GDP per capita would affect contemporaneous educational levels.[18]

Next we estimate an ordered generalized Probit model in which country clusters are ordered by income per capita levels (with cluster 1 being the lowest group, and cluster 4 the highest), and eight sectoral indicators are included as potential determinants of the probability that a country belonging to a particular cluster may jump to a higher income cluster. These sectors are Capital Markets, Education, Health, Infrastructure, Innovation, Integration and Trade, Labor Markets, and Telecommunications.[19]

Notice that this estimation technique allows for different coefficients accompanying sectoral indicators, depending on the particular cluster being analyzed. This is done, for any

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[15] Once sectoral indicators are constructed, they are normalized once again. This is done so that each sectoral indicator has a zero mean and unit variance (since individual indicators in one sector are likely correlated, their average may have a variance different from one). Keeping a unit variance for the sectoral indicator is relevant for the exercises to be performed later.

[16] This means that one would first observe changes in the aggregate sectoral indicator that affect income per capita in subsequent periods.

[17] We do find PPP-adjusted GDP per capita to be positively cointegrated with the aggregate indicator of sectors affecting productivity.

[18] However, this is not the case for all indicators. Some areas such as capital markets may be susceptible to shocks to GDP per capita, and that is why all variables in the model have been lagged to reduce potential endogeneity.

[19] See Appendix Table A1 for a description of the indicators comprising each of these sectors.

particular cluster, by splitting the sample into observations belonging to that income per capita cluster and observations belonging to all other higher income per capita clusters, thus exploiting differences between countries in one cluster and those in higher clusters. This is done for every cluster (except the last one), and estimation of all three models is carried out jointly. Since our estimation has four country clusters, coefficients can be estimated for the first three clusters, which are those in which countries can jump to a higher income cluster. Given that there is a good chance that residuals of any particular country are correlated, estimations are carried out using clustered errors to assess significance.

Results are shown in Table 1, with the first coefficient column belonging to Cluster 1 countries, the second column belonging to Cluster 2 countries, and the third column belonging to Cluster 3 countries.[20] This estimation tests for coefficient restrictions to check whether any sector's coefficients can be restricted to be the same across all clusters. It turns out that the two sectors that call for this restriction are Health and Telecommunications.[21] In order to control for global and common external conditions, we include a measure of the VIX index.[22,23,24]

[20] Standard deviations of coefficient estimates in Table 1 are calculated using clustered errors at the country level.
[21] Likelihood ratio tests were used to determine the use of these restrictions in the estimation.
[22] The VIX index is a market volatility index which shows the market's expectation of 30-day volatility for a wide range of S&P 500 index options. It is widely used as a measure of international market risk conditions, capturing changes in investor risk appetite.
[23] We attempted to include time dummies to control for all common factors, but many of them seem to be collinear and were dropped from estimations. For that reason, we opted instead for using the VIX index to control for common global conditions.
[24] This estimation includes contemporaneous values of the VIX index, and a common coefficient of the VIX index for all groups, given results from likelihood ratio tests. A similar estimation with lagged values of the VIX is included in Appendix Table A4. Qualitative results do not change for this alternative estimation.

Table 1. Results of Generalized Ordered Probit Model

	(1) Cluster 1	(2) Cluster 2	(3) Cluster 3
Capital Markets	0.418	-0.174	1.709***
	(0.728)	(0.466)	(0.624)
Education	1.117**	-0.133	-0.772
	(0.533)	(0.292)	(0.466)
Health	0.681**	0.681**	0.681**
	(0.321)	(0.321)	(0.321)
Infrastructure	0.470	-0.461	3.951***
	(0.864)	(0.361)	(1.077)
Innovation	3.428	1.520	-0.293
	(1.964)	(1.015)	(0.560)
Integration & Trade	1.391	1.289**	-0.291
	(1.185)	(0.560)	(0.261)
Labor	-0.526	1.093***	-0.588
	(1.443)	(0.386)	(0.462)
Telecommunications	0.166	0.166	0.166
	(0.294)	(0.294)	(0.294)
VIX	-0.040***	-0.040***	-0.040***
	(0.009)	(0.009)	(0.009)
Observations	396	396	396
Country Cluster	47	47	47

Note: Coefficient standard deviations are estimated using clustered errors at the country level.
***Significant at the 1% level, **Significant at the 5% level.

Interpretation of the results in Table 1 indicates that Education and Health are statistically significant at the 5 percent level for Cluster 1 countries (Innovation only at the 10 percent level), while Labor, Integration and Trade, as well as Health are significant at the 1 percent level for Labor, and at the 5 percent level for Integration and Trade and Health for Cluster 2 countries. The highest income per capita group in Latin America and the Caribbean (in Cluster 3) shows statistically significant results for Capital Markets (at the 1 percent level), Infrastructure (at the 1 percent level) and Health (at the 5 percent level). These results point to the need to focus on different priorities for countries belonging to different income groups. We call these significant sectors Priorities for Productivity and Income (PPIs). There seems to be some common sense in the determination of priorities captured by this methodology: in lower income countries, basic priorities such as education and health seem to matter the most, whereas in lower-middle income countries priorities change to labor markets and integration, and in middle income countries the focus changes once again, this time to strengthening access to credit and infrastructure.

Since coefficients belong to standardized sectoral indicators, their value can be read directly in order to rank priorities within each cluster. For example, a 1 standard deviation rise in Infrastructure for a country in Cluster 3 increases the probability of reaching Cluster 4 by more than a 1 standard deviation increase in either Capital Markets or Health. As a result, this methodology delivers a set of PPIs that can be identified and ranked for each cluster of countries.

5. Robustness and Goodness of Fit

Regarding goodness of fit and robustness of these results, a series of calculations were carried out along two dimensions. First, a battery of goodness-of-fit measures were computed. These include a count pseudo-R^2, which treats any observation with a predicted probability of 0.5 or greater as having a predicted outcome of 1 (or 0 otherwise) and then computes the number of correct matches as a share of total observations. We do this by using the corresponding cluster estimation for each observation, depending on the cluster to which it belongs.[25] This measure yields a value of 95.6 percent, indicating highly consistent predictions relative to the data. Using a more stringent adjusted pseudo-R^2 measure, accounting for the fact that some outcomes have a larger occurrence rate, yields a value of 72.5 percent, indicating relatively good performance even when adjusting for the occurrence characteristics of the sample. Another commonly used measure for Probit models is McFadden's indicator, which computes goodness of fit by comparing the log likelihood of the full model relative to that containing only an intercept. This measure yields a value of 72.9 percent, very similar to that of the adjusted pseudo-R^2.

The second dimension involves robustness analysis of the estimated coefficients. We assess this by performing the same estimation as the one presented above 5,000 times, but randomly dropping one country-year observation at a time. Figures A2 through A10 show the resulting histograms of the estimated coefficients for each of the three clusters. All 27 coefficients show highly concentrated distributions around the estimated parameters of the original estimation including the whole sample. Summary statistics portraying these results are reproduced in Table A5.

On average, almost 84 percent of estimated coefficients fall inside a window comprised of ½ a standard deviation to each side of the coefficient of the full sample estimation (see Table

[25] Each cluster estimation calculates the probability that a country will belong to the group of higher income per capita clusters—or obtain a value of 1 in terms of the Probit. If that probability is 0.5 or higher, a value of 1 is assigned to that observation.

A5, column 1), indicating high concentration. Moreover, on average 99.9 percent of the time the estimated coefficients generated randomly by changing the sample coincide with the coefficient of the original estimation in terms of being significant (or not significant) at the 5 percent level (see Table A5, column 2). In order to measure the concentration of these distributions around the coefficient of the original estimation in each sector, we compute a measure of excess kurtosis, as well as a measure of excess kurtosis adjusted for skewness, relative to that of a normal distribution.[26,27] All measures of excess kurtosis for each of the 27 distributions are quite high, ranging from 7.4 to 246.7 for standard kurtosis, with average excess kurtosis yielding 83.2 (see Table A5, column 3). Even after adjusting for skewness, adjusted-kurtosis measures range from 6.9 to 161.6, with average excess kurtosis representing 60.8 (see Table A5, column 4).

A similar exercise was performed by running 1,000 estimations, this time dropping *all* observations for one particular country at a time. Results go in the same direction: 77 percent of estimated coefficients fall inside a window comprised of ½ a standard deviation to each side of the coefficient of the full sample estimation, and 97.7 percent of the time the estimated coefficients generated randomly by dropping one country at a time coincide with the coefficient of the original estimation in terms of being significant (or not significant) at the 5 percent level. Standard excess kurtosis ranges from 1.49 to 37.9, with average excess kurtosis yielding 11.8. Adjusted-kurtosis measures range from 0.58 to 18.2, with average excess adjusted-kurtosis representing 7.2.

All these results point to heavily concentrated coefficient distributions around the original estimates. Moreover, these randomly generated coefficients share significance with those of the original estimation 97.7 to 100 percent of the time—depending on the type of robustness exercise—thus pointing to the robustness of original estimates.

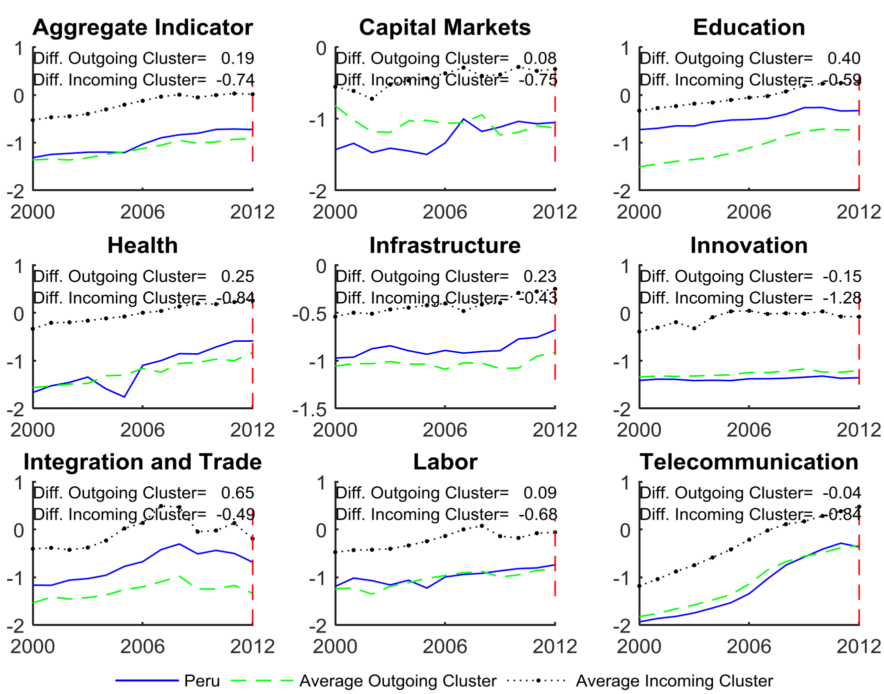
[26] It is well known that a property of skewed distributions is that they have larger measures of kurtosis. We adjust for this fact using Blest's measure of adjusted kurtosis (see Blest, 2003).
[27] Excess kurtosis is defined as kurtosis of the distribution minus that of a normal distribution (which has a value of 3).

6. An Application: The Case of Peru

We now use the results of our estimations to study the case of Peru, also providing some contrasting examples from Colombia. Analysis of this case is helpful not only to see what the methodology can deliver when put to use, but also to highlight some differences in selecting priorities with other methods and benchmarks.

Peru is a recent entrant to Cluster 3, having reached it in 2012, and it is the lowest income per capita member of this group, which includes Latin America's biggest economies as well as Portugal and several Eastern European countries such as the Czech Republic and Poland. Peru's evolution on the road towards Cluster 3 is shown in Figure 2, which contains each of the eight sectoral indicators as well as the aggregate indicator spanning the period 2000-2012. Peru's indicators are contrasted against the mean for its own group before jumping, or outgoing group (Cluster 2, excluding Peru) and the mean of the better, or incoming, group (Cluster 3). Two sectors in particular show a significant narrowing of gaps vis-à-vis the mean of Cluster 3 between 2000 and 2012: Integration and Health. Both of these sectors coincide with PPIs for Cluster 2, which helps explain Peru's success in reaching Cluster 3.

Figure 2. Evolution of Peru's Sectoral Indicators: Comparison with Mean of Outgoing Cluster and Mean of Incoming Cluster



Source: IDB, Research Department.

However, given this recent entry, it is expected that Peru's probability of jumping to Cluster 4 should be low. As a matter of fact, given that all of Peru's sectoral indicators in 2012 (the latest year available for all 34 individual indicators) lie below the mean of its new cluster, it is easy to see why the model predicts a probability close to zero of Peru jumping to Cluster 4 (see Table 2). Yet one can ask how much that probability would change if ½ a standard deviation were allocated to each of the PPIs identified for Cluster 3 countries. We do not choose the size of this allocation arbitrarily: the average distance in each of the sectors for countries across the different clusters is in the neighborhood of 0.5. For the case of Peru, this means allocating ½ standard deviation to Infrastructure, ½ standard deviation to Capital Markets, and another ½ standard deviation to Health, for a total allocation of 1½ standard deviations. The reason that we split the total allocation into three ½ a standard deviations across different PPIs is that allocating 1 or 1½ standard deviations to any particular PPI would imply a very large increase in that PPI, something that seems difficult to achieve.[28] Once the ½ standard deviation allocation in each of the abovementioned sectors is introduced, Peru's probability of jumping to Cluster 4 is still a low 9 percent. Even if this probability is low, there is something useful to learn about the model: increasing each PPI *individually* does very little to increase this probability. For example, by increasing each of the PPIs individually by ½ a standard deviation and adding up their individual contribution to the probability—keeping other PPIs at their original levels—yields a probability value of 0.61 percent. Yet the joint impact of increasing all three PPIs *simultaneously* by ½ a standard deviation brings the probability up to 9 percent, highlighting the relevance of interactions among sectors when deciding on a strategy to increase income per capita levels.

Having a low probability of reaching cluster 4 makes sense for the case of Peru, because this country has only very recently reached Cluster 3, and it still has a long way to go before it can improve sectoral indicators to levels similar to those of Cluster 4. To see this, consider the values of each of the sectoral indicators in Peru as of 2012 compared to the average of its own group (Cluster 3, excluding Peru) and the average of the next income per capita group, Cluster 4. These figures are shown in Table 2, together with the gaps between Peru and the average of its own group as well as those between Peru and the average of the next group (columns 4 and 5). Sectors are ranked according to the size of the gaps between Peru and the average of the next

[28] For example, for the case of Peru, an increase of 1 standard deviation in Education would imply making improvements in that sector so that it reaches Canada levels.

group. This is done for illustration purposes only to contrast results of the Probit priorities model with those stemming from gap analysis.[29]

Notice that in this case, the three largest gaps occur in Innovation, Capital Markets, and Infrastructure, two of which coincide with the PPIs defined by our methodology. However, there are large differences in the ordering of priorities by gaps when these are calculated with respect to the average of Peru's own group—a measure akin to methodologies that measure gaps relative to predicted values based on Peru's GDP per capita. In this case, the three largest gaps are in Innovation, Telecommunications, and Health, and only one of these three priorities coincides with PPIs.

Table 2. Comparison by Sector: Peru's Own Cluster and Next Cluster (Means)

	2012 Values			Evaluation	
	Peru's Normalized Value	Mean Own Group	Mean Next Group	Gap with Own Group	Gap with Next Group
Innovation	-1.36	-0.08	0.73	-1.28	-2.09
Capital Markets	-1.05	-0.31	0.99	-0.74	-2.04
Infrastructure	-0.68	-0.25	1.10	-0.43	-1.78
Health	-0.59	0.25	1.03	-0.84	-1.62
Telecommunication	-0.37	0.48	1.20	-0.85	-1.57
Labor	-0.74	-0.06	0.72	-0.68	-1.46
Education	-0.33	0.26	0.94	-0.59	-1.27
Integration and Trade	-0.69	-0.19	0.29	-0.50	-0.98
Aggregate Indicator	-0.73	0.01	0.88	-0.74	-1.61

Source: IDB, Research Department.

These differences are starker in the case of Colombia (see Table 3), which also belongs to Cluster 3 and thus shares PPIs with Peru. When Colombia's gaps are compared with the average of its own cluster, the largest three occur in Education, Labor, and Integration, none of which

[29] However, our methodology does not rely on gap analysis to determine priorities. Recall that priorities stemming from the Probit model are selected by their ability to affect the likelihood of jumping to a higher income per capita group, and not by the size of gaps.

coincide with PPIs.[30] Thus, standard gap analysis may yield quite different results compared to PPIs, because gaps do not necessarily indicate the value of the restriction generated by low performance in any particular sector, something that the PPI methodology indirectly addresses by measuring which sectors are more relevant in maximizing the chances of jumping to a higher income per capita cluster.

Table 3. Comparison by Sector: Colombia's Own Cluster and Next Cluster (Means)

	2012 Values			Evaluation	
	Colombia's Normalized Value	Mean Own Group	Mean Next Group	Gap with Own Group	Gap with Next Group
Infrastructure	-0.83	-0.25	1.10	-0.58	-1.93
Labor	-1.03	-0.06	0.72	-0.97	-1.75
Education	-0.72	0.26	0.94	-0.98	-1.66
Capital Markets	-0.56	-0.31	0.99	-0.25	-1.55
Innovation	-0.74	-0.08	0.73	-0.66	-1.47
Health	-0.37	0.25	1.03	-0.62	-1.40
Telecommunication	-0.09	0.48	1.20	-0.57	-1.29
Integration and Trade	-0.89	-0.19	0.29	-0.70	-1.18
Aggregate Indicator	-0.65	0.01	0.88	-0.66	-1.53

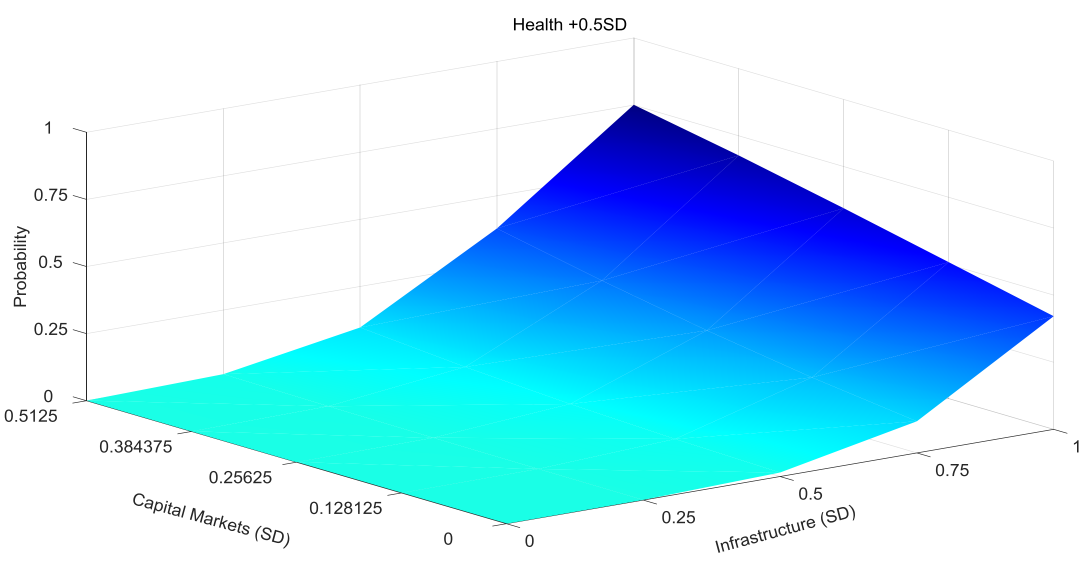
Source: IDB, Research Department.

Another way to estimate the usefulness of PPIs in any particular country is to ask how many standard deviations would be needed to reach a large probability of reaching a higher cluster. For the analysis of Peru, that probability was set at 75 percent. Results show that Peru would reach that probability level if it were able to invest 2.01 standard deviations, allocating 1 standard deviation to Infrastructure, 0.51 standard deviations to Capital Markets, and ½ a standard deviation to Health.[31] Notice the non-linear impact that is present in the model: in the

[30] When comparing gaps against the next cluster, only Infrastructure coincides with identified PPIs.
[31] We follow the rule of first allocating ½ a standard deviation to each sector, and if that is not enough to reach a probability level of 75 percent, we keep allocating ½ a standard deviation from the most productive sector (in this

previous exercise we had allocated only ½ a standard deviation to each PPI, resulting in a probability of 9 percent, but now increasing Infrastructure by an *additional* ½ a standard deviation (for a total of 1 standard deviation) and an *additional* 0.01 standard deviation in Capital Markets (for a total of 0.51 standard deviation) boosts the probability of jumping to the next cluster to 75 percent. This can be seen graphically in Figure 3 which shows—departing from Peru's probability by 2012, which is basically zero—how the probability increases as Infrastructure is increased by up to 1 standard deviation and the Capital Markets indicator is increased by up to 0.51 standard deviations, with Health always set to a ½ a standard deviation increase. The impact of the increase in Health is not shown directly, but implicitly through the way that Infrastructure and Capital Markets affect the probability of jumping to an upper cluster. As argued previously, the impact of Infrastructure and Capital Markets on that probability is not independent of the level of Health. Figure 3 shows that Infrastructure has the upper hand in terms of increasing the probability of reaching a higher cluster, highlighting the value of this particular PPI for countries in this cluster. However, the key message here is that its impact is significantly increased when Capital Markets are developed concomitantly.

Figure 3. Peru: Probability of Jumping to the Next Cluster for Different Increases in PPIs (Measured in Standard Deviations)



Source: IDB, Research Department.

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case, Infrastructure) to the second most productive sector (in this case, Capital Markets), and so on until a probability of 75 percent is reached.

7. Conclusions

This study is a first contribution to prioritization across productivity determinant capabilities that attempts to obtain the equivalent of a "shadow price" for each of these capabilities, which differs depending on income per capita clusters.[32] Results from this study point to the relevance of these determinants in affecting the success a country may have in reaching higher income per capita groups. The prioritization of these determinants, spanning different sectors, seems to be specific to the income per capita group a county belongs to. Moreover, our empirical estimates reveal that interactions among sectors are important when it comes to increasing the probability of climbing up the income per capita ladder, reflecting the existence of complementarities across sectors, thus indicating that the *joint* improvement of some of them may be necessary before effects on income per capita are noticeable. Results also indicate that the identification of priorities—by looking at the impact that sectors have in increasing the likelihood of advancing to a better income per capita group—may or may not coincide with the size of sector gaps, as larger gaps do not necessarily capture the relevance of sectoral restrictions and their interactions.

[32] Ideally, a much larger time span than the one used here should be used to accumulate a larger set of experiences. However, important data gaps exist in sectoral indicators that make it almost impossible to apply this methodology to a larger time series data set.

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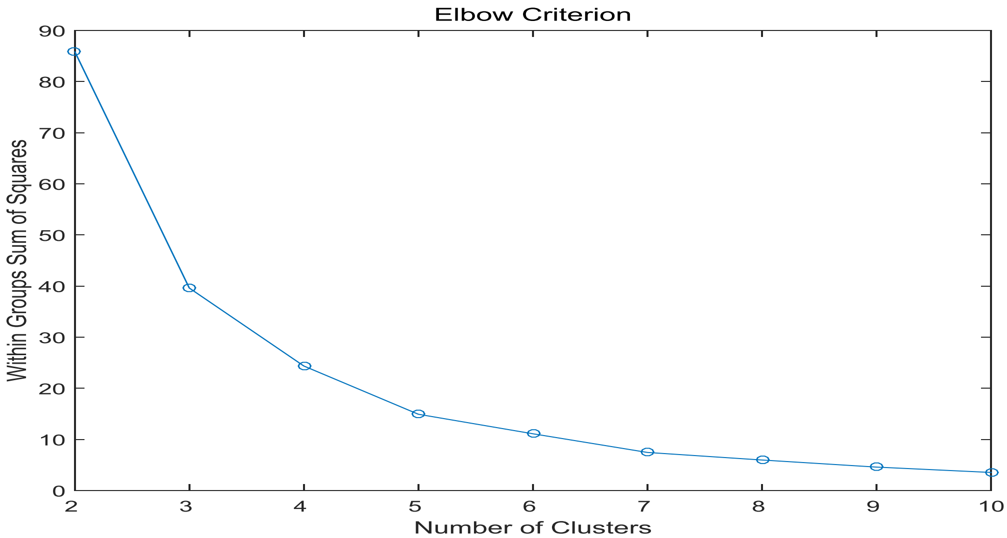
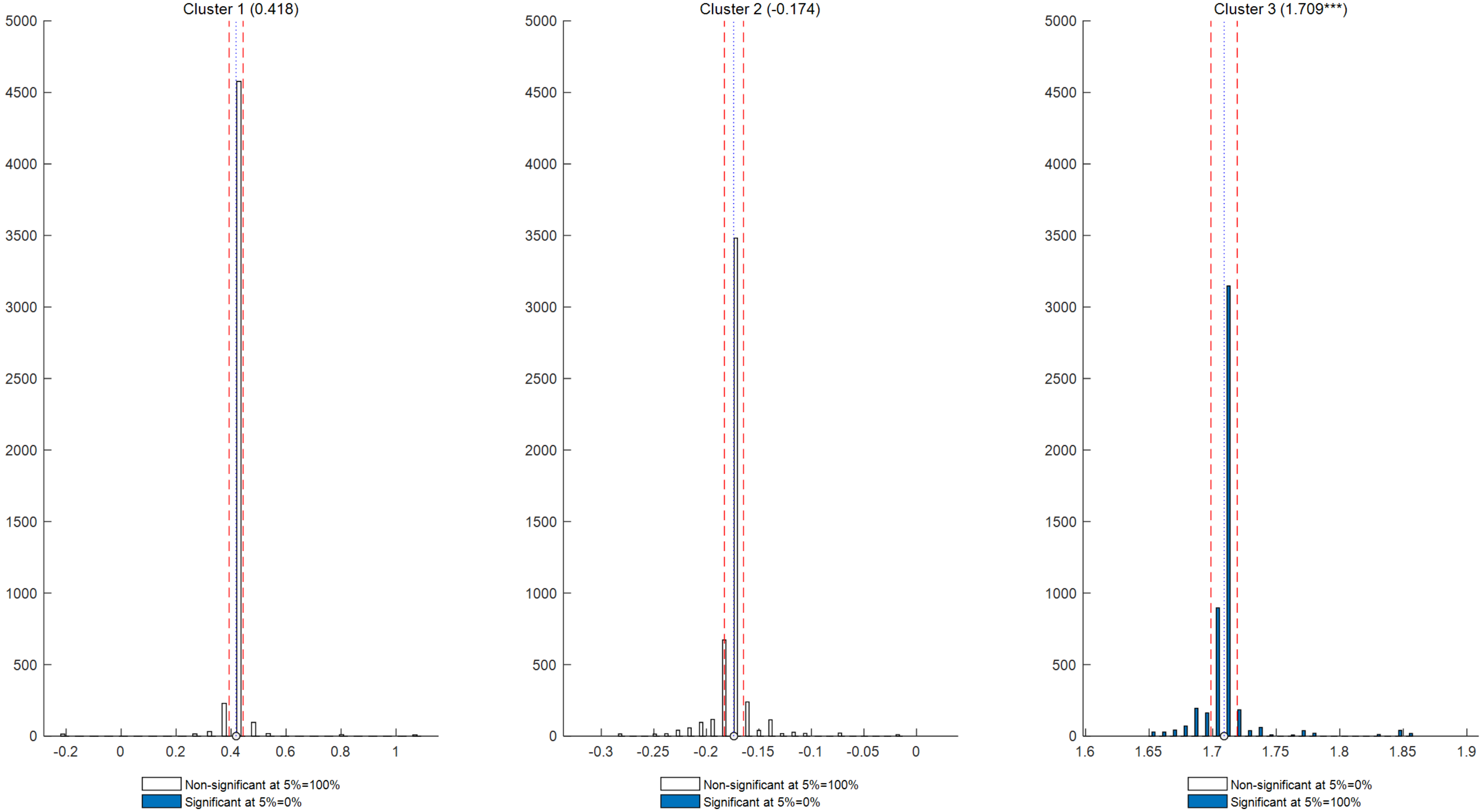
Appendix

Figure A1. Criterion for Selection of Optimal Number of Clusters



Source: Authors' estimates.

Figure A2. Histogram of Capital Markets Coefficients for Each of the Clusters



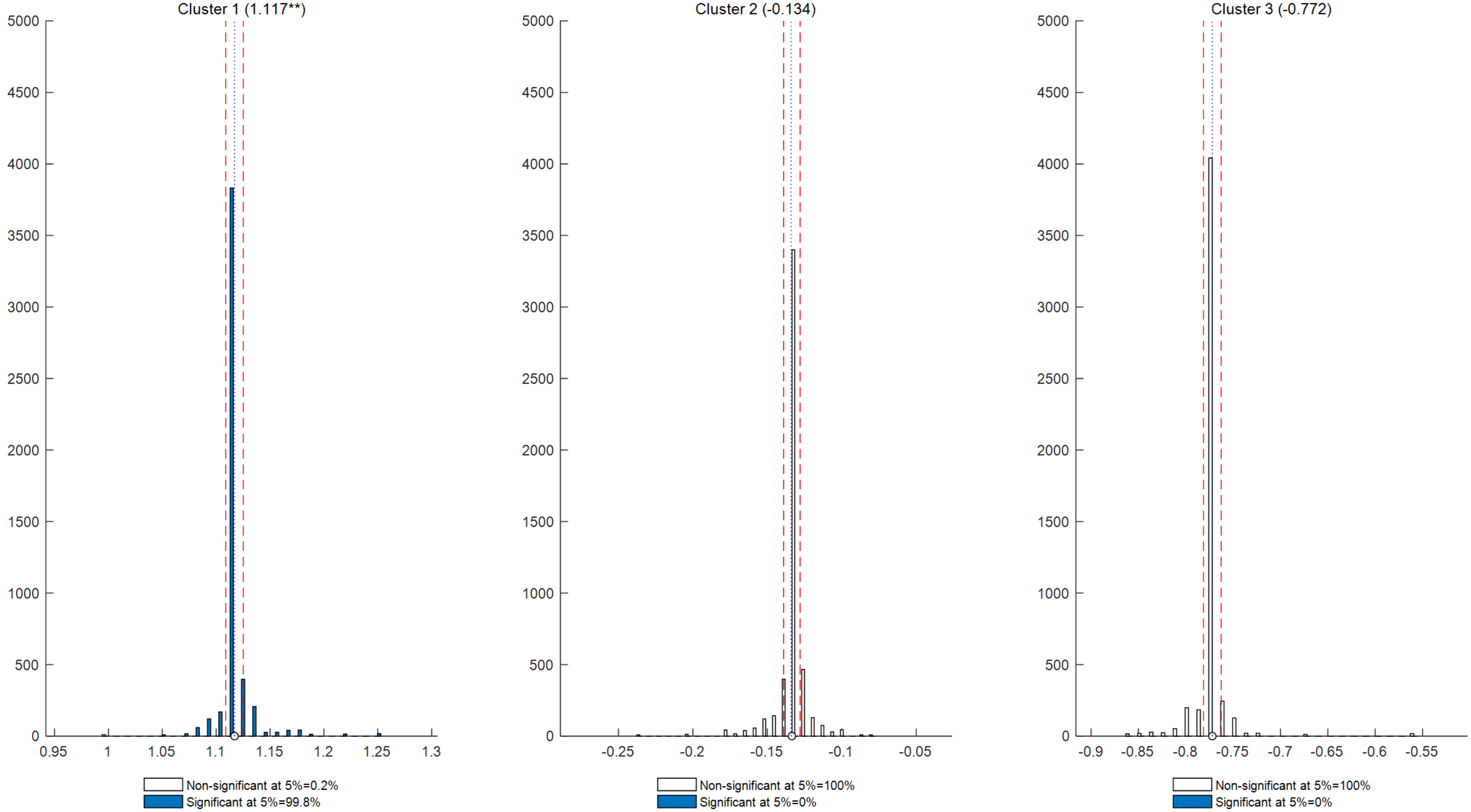
91.7% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 134.45.

78.2% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 21.55.

83.6% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 17.57.

Note: Each figure plots the sample median (dotted line) and a 1 std deviation window (dashed lines) centered around the regression coefficient (circle over the x axis). Significance of the coefficient in the original regression is indicated in parenthesis next to the cluster title. Coefficient distributions are obtained after runing 5000 estimations, dropping randomly one country-time observation at a time.

Figure A3. Histogram of Education Coefficients for Each of the Clusters



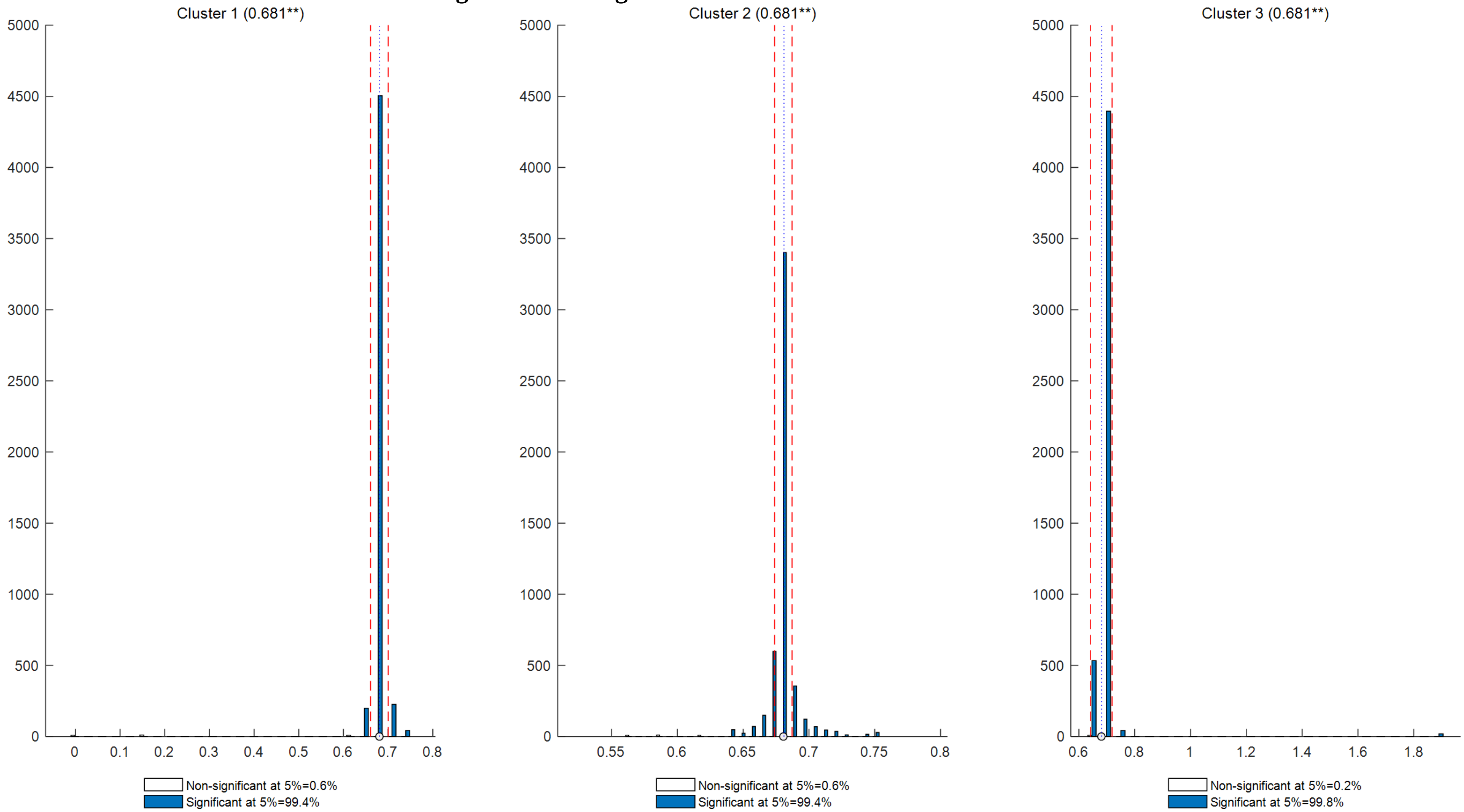
81.6% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 27.16.

78% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 19.23.

85.4% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 56.09.

Note: Each figure plots the sample median (dotted line) and a 1 std deviation window (dashed lines) centered around the regression coefficient (circle over the x axis). Significance of the coefficient in the original regression is indicated in parenthesis next to the cluster title. Coefficient distributions are obtained after runing 5000 estimations, dropping randomly one country-time observation at a time.

Figure A4. Histogram of Health Coefficients for Each of the Clusters



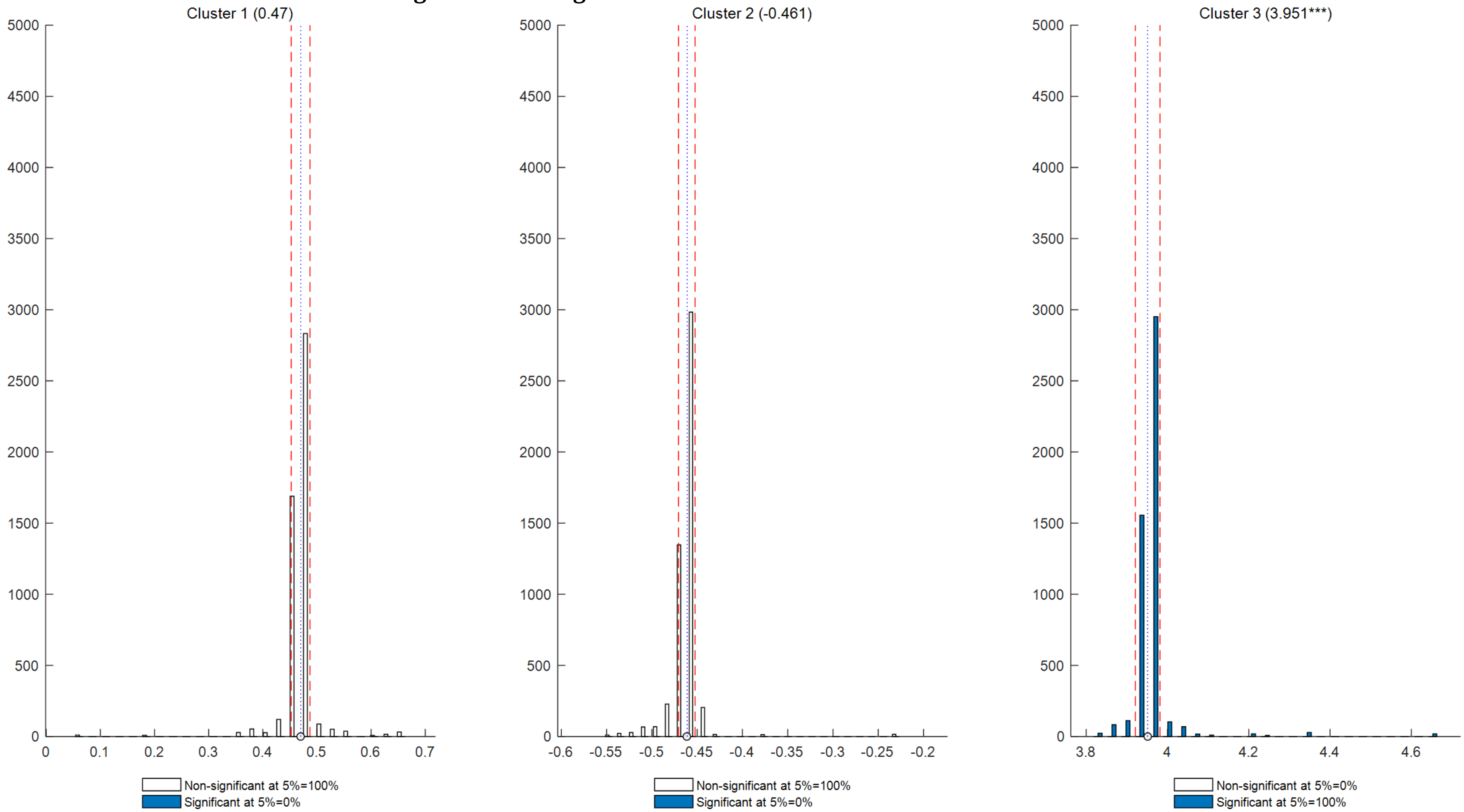
92.5% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 157.07.

75.5% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 23.38.

96.9% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 161.59.

Note: Each figure plots the sample median (dotted line) and a 1 std deviation window (dashed lines) centered around the regression coefficient (circle over the x axis). Significance of the coefficient in the original regression is indicated in parenthesis next to the cluster title. Coefficient distributions are obtained after runing 5000 estimations, dropping randomly one country-time observation at a time.

Figure A5. Histogram of Infrastructure Coefficients for Each of the Clusters



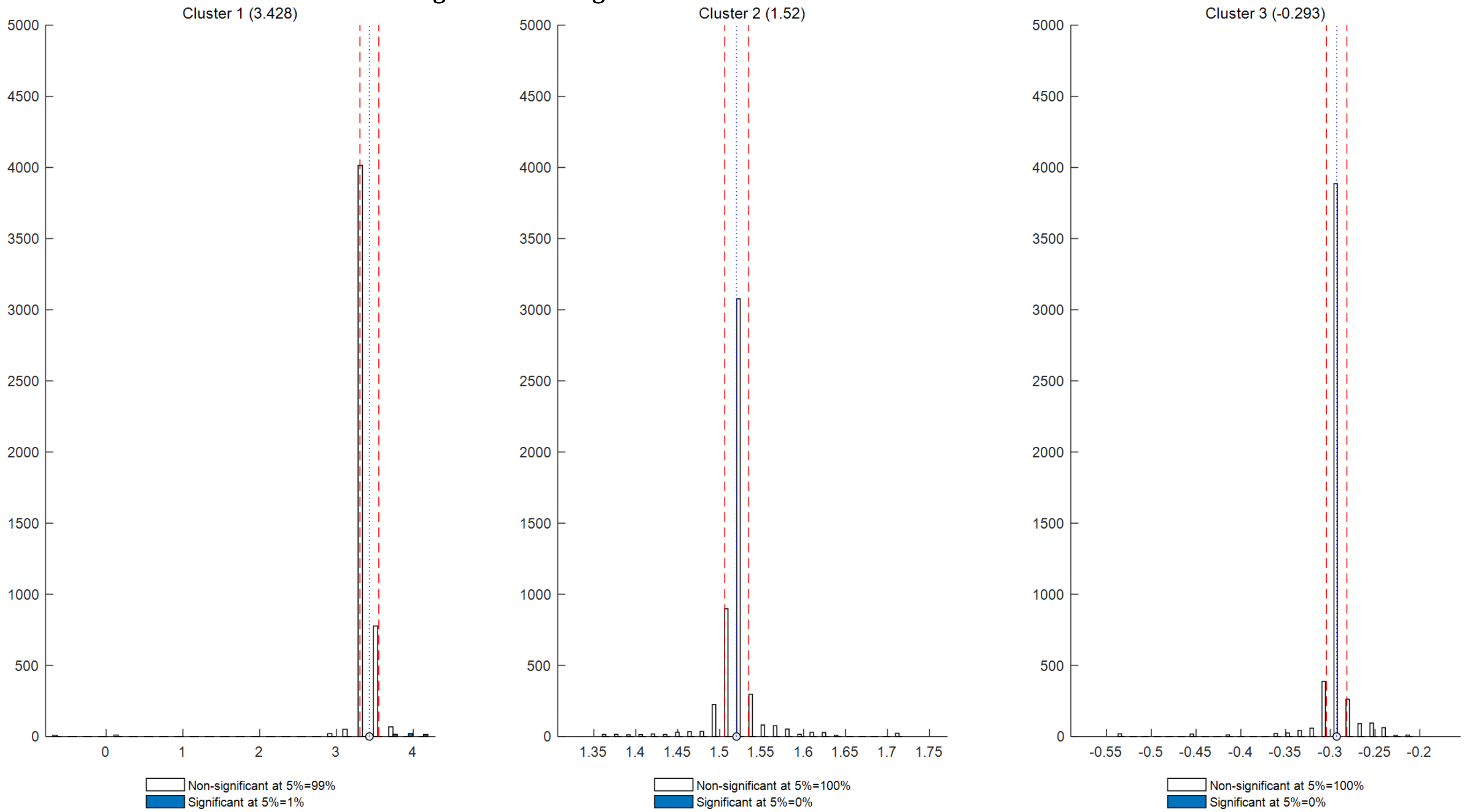
85.7% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 52.92.

83% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 70.49.

88.8% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 50.32.

Note: Each figure plots the sample median (dotted line) and a 1 std deviation window (dashed lines) centered around the regression coefficient (circle over the x axis). Significance of the coefficient in the original regression is indicated in parenthesis next to the cluster title. Coefficient distributions are obtained after runing 5000 estimations, dropping randomly one country-time observation at a time.

Figure A6. Histogram of Innovation Coefficients for Each of the Clusters



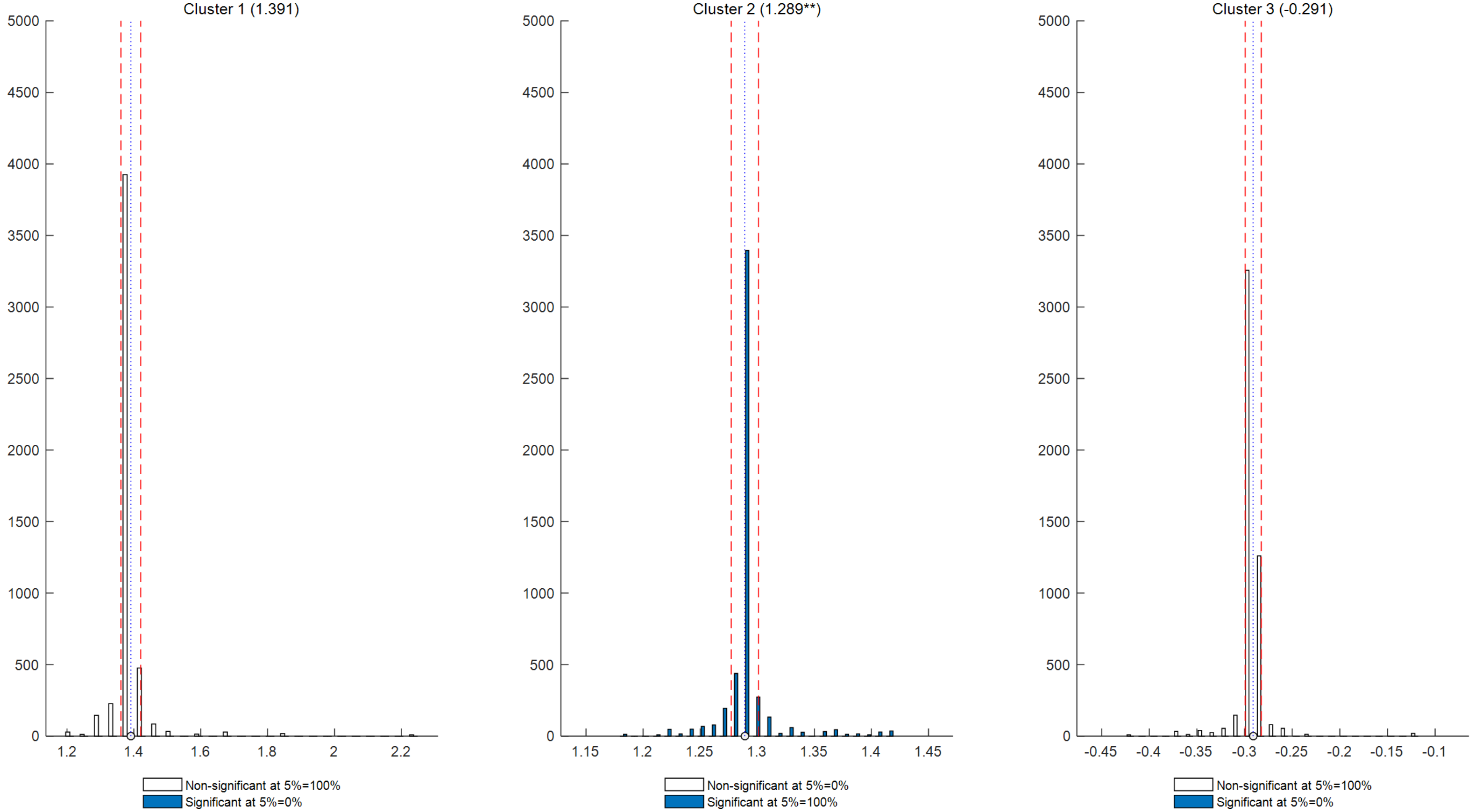
92.3% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 141.68.

78.4% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 16.83.

85.2% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 40.33.

Note: Each figure plots the sample median (dotted line) and a 1 std deviation window (dashed lines) centered around the regression coefficient (circle over the x axis). Significance of the coefficient in the original regression is indicated in parenthesis next to the cluster title. Coefficient distributions are obtained after runing 5000 estimations, dropping randomly one country-time observation at a time.

Figure A7. Histogram of Integration and Trade Coefficients for Each of the Clusters



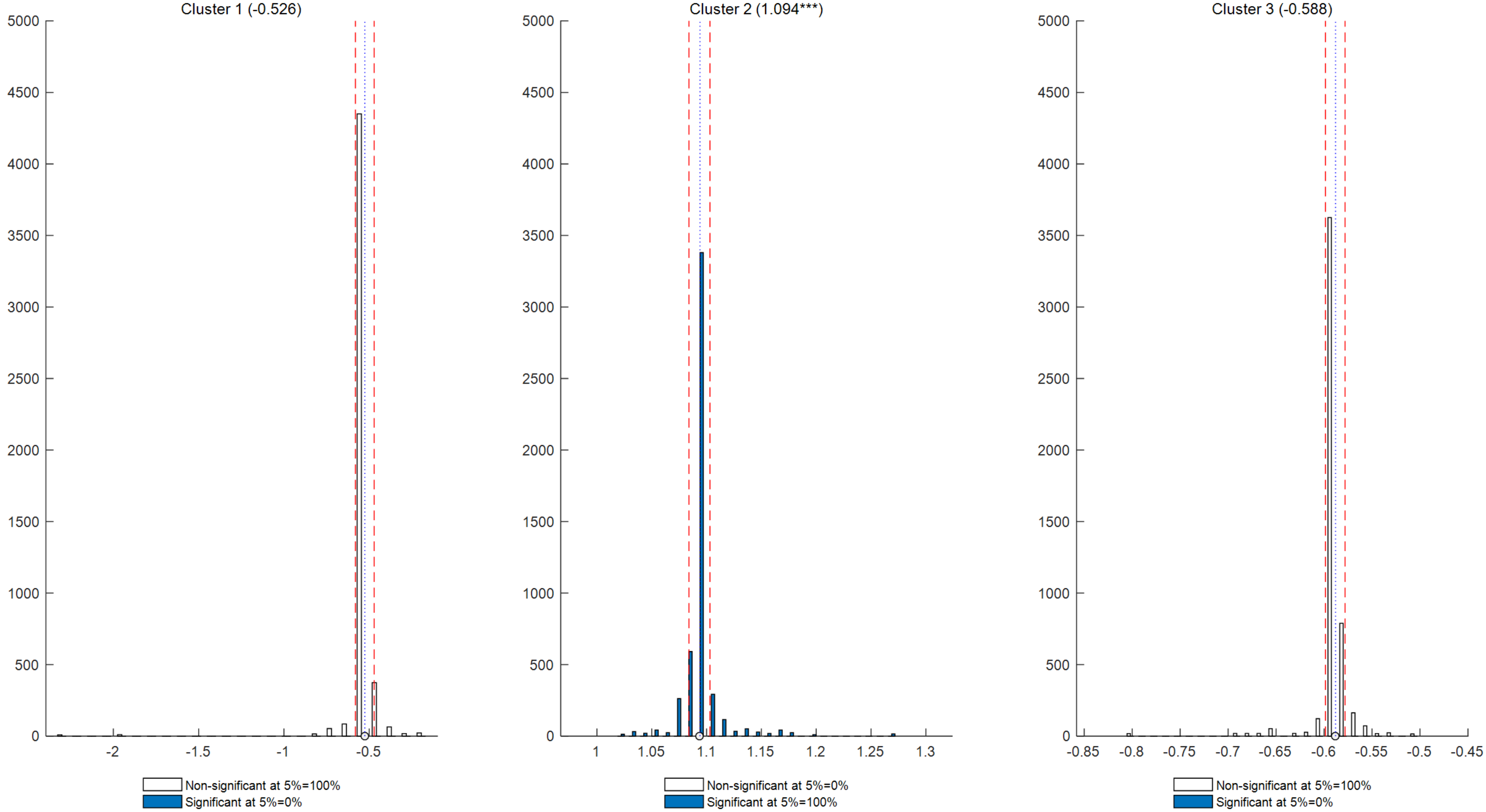
85.7% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 68.37.

78.1% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 9.31.

83.5% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 48.92.

Note: Each figure plots the sample median (dotted line) and a 1 std deviation window (dashed lines) centered around the regression coefficient (circle over the x axis). Significance of the coefficient in the original regression is indicated in parenthesis next to the cluster title. Coefficient distributions are obtained after runing 5000 estimations, dropping randomly one country-time observation at a time.

Figure A8. Histogram of Labor Coefficients for Each of the Clusters



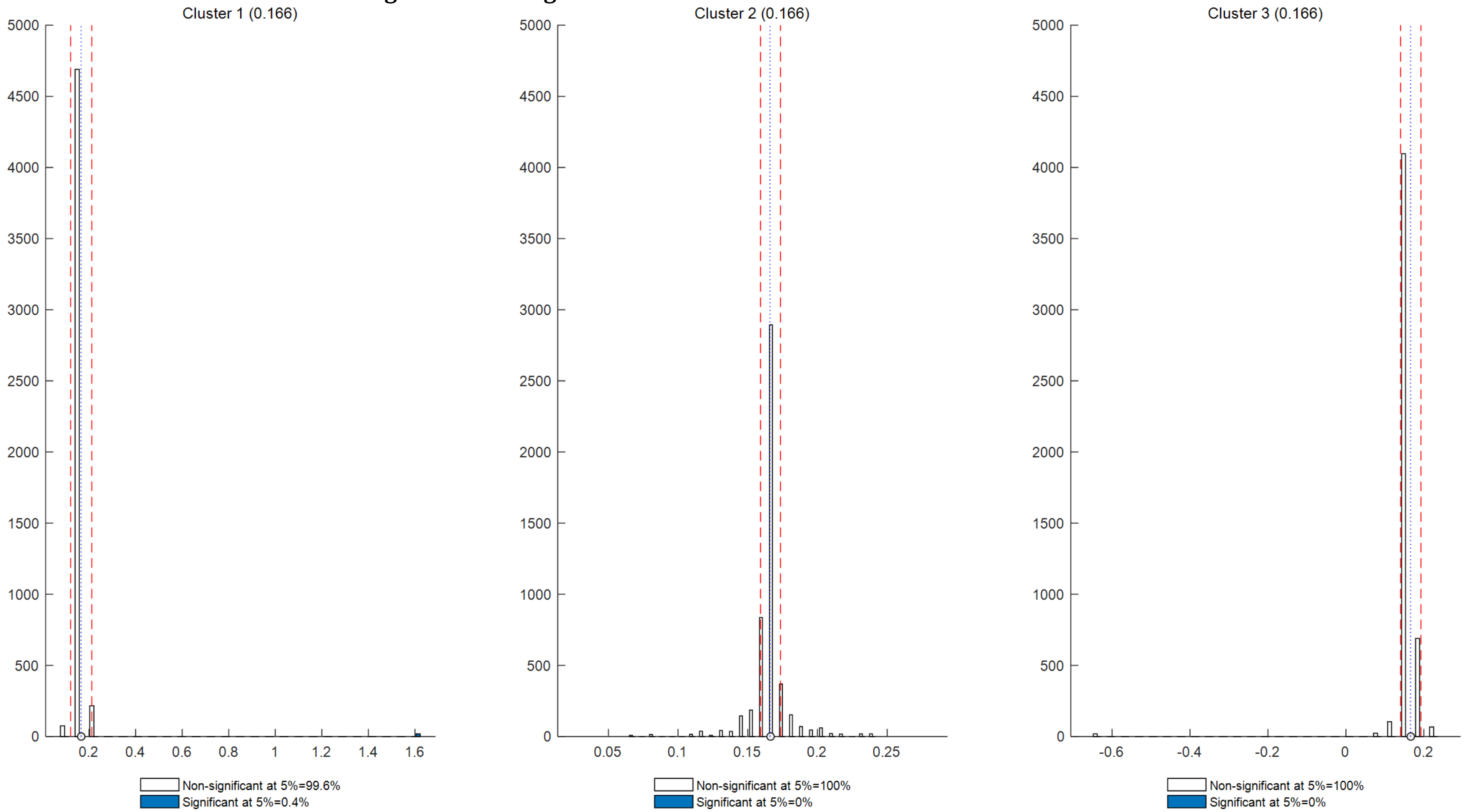
92% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 124.42.

78.6% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 22.23.

86.4% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 37.28.

Note: Each figure plots the sample median (dotted line) and a 1 std deviation window (dashed lines) centered around the regression coefficient (circle over the x axis). Significance of the coefficient in the original regression is indicated in parenthesis next to the cluster title. Coefficient distributions are obtained after runing 5000 estimations, dropping randomly one country-time observation at a time.

Figure A9. Histogram of Telecommunication Coefficients for Each of the Clusters



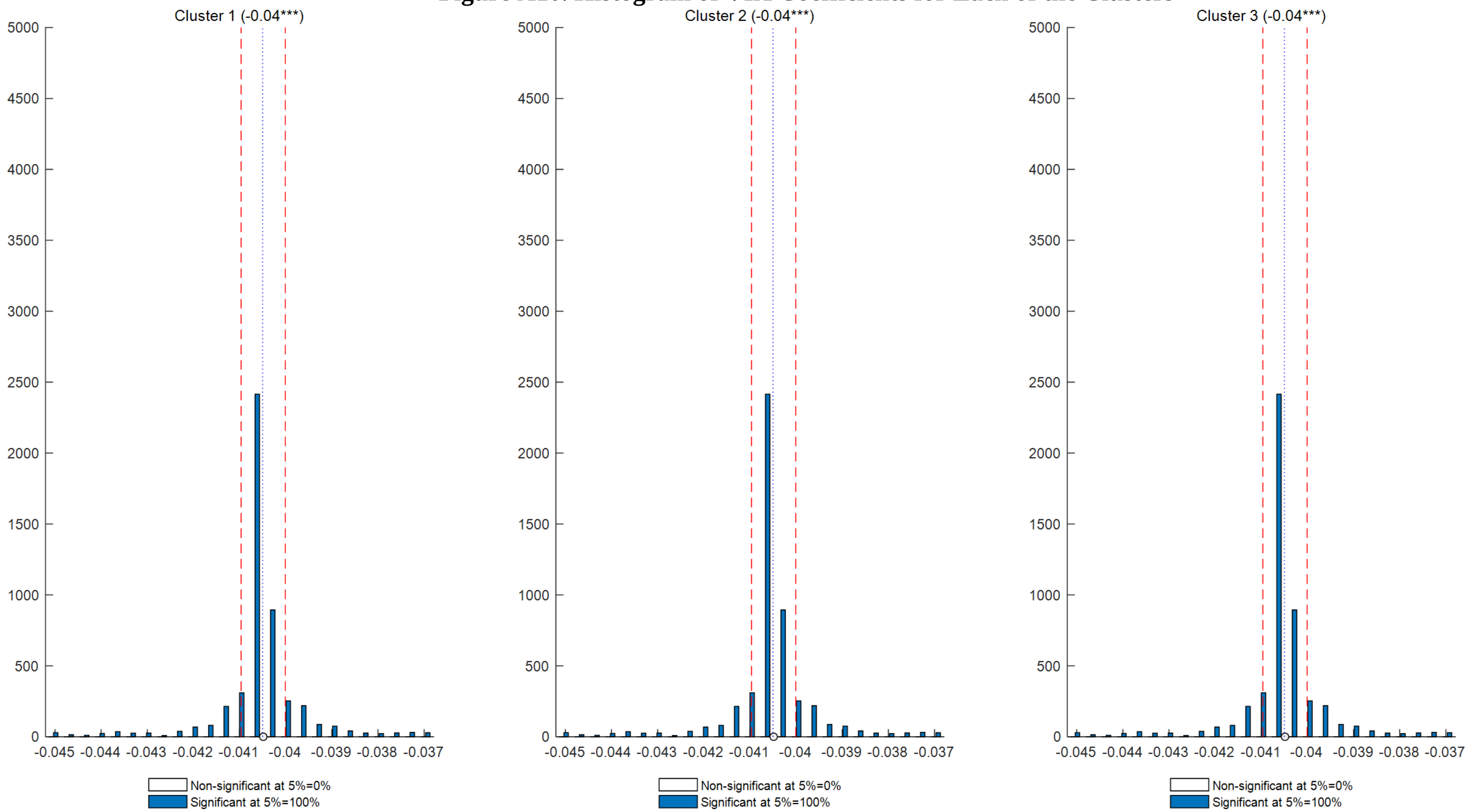
97.5% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 161.19.

74.3% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 13.37.

93.1% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 146.55.

Note: Each figure plots the sample median (dotted line) and a 1 std deviation window (dashed lines) centered around the regression coefficient (circle over the x axis). Significance of the coefficient in the original regression is indicated in parenthesis next to the cluster title. Coefficient distributions are obtained after runing 5000 estimations, dropping randomly one country-time observation at a time.

Figure A10. Histogram of VIX Coefficients for Each of the Clusters



71.2% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 6.93.

71.2% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 6.93.

71.2% of coefficients fall within 0.5 std deviation of the main regression coefficient.
Excess kurtosis adjusted for skewness is 6.93.

Note: Each figure plots the sample median (dotted line) and a 1 std deviation window (dashed lines) centered around the regression coefficient (circle over the x axis). Significance of the coefficient in the original regression is indicated in parenthesis next to the cluster title. Coefficient distributions are obtained after runing 5000 estimations, dropping randomly one country-time observation at a time.

Table A1. Individual Indicators Used for Construction of Sectoral Indicators

Sector		Indicator	Source
		GDP per capita, PPP (constant 2011 international $)	WEO, IMF
Capital Markets	1	Domestic credit to private sector by banks (% of GDP)	WDI, World Bank
	2	Lending interest rate (% Real)*	WDI, World Bank, Economist Intelligence Unit, Bloomberg and WEO, IMF
	3	Market capitalization of listed companies (% of GDP)	WDI, World Bank
	4	Property Rights Index	Economic Freedom of the World Index Database, Fraser Institute
	5	Rule of Law	WDI, World Bank
Education	6	Education expenditure (% of GNI)	WDI, World Bank
	7	Net rate of enrollment, pre-school	UIS, UNESCO and OCDESTATS
	8	Population age 25+ with secondary or tertiary schooling (% completed)	Barro and Lee dataset (June 2014 update)
	9	Population age 25+ with no education (% of total population)*	Barro and Lee dataset (June 2014 update)
Health	10	Life expectancy at birth	WDI, World Bank
	11	Public expenditure on health (% GDP)	WDI, World Bank
	12	Infant mortality rate under-1 (per 1000 live births)*	WDI, World Bank
	13	Mortality rate under-5 (per 1000 live births)*	WDI, World Bank
	14	Immunization, measles (% of children ages 12-23 months)	WDI, World Bank
	15	Maternal mortality rate (modeled estimate, per 100000 live births)*	WDI, World Bank
Infrastructure	16	Road density (km of road per 100 sq. km of land area)	WDI, World Bank, CIA, and Freight Logistics Yearbook, IDB
	17	Road safety (number of fatalities per 100,000 people)*	IDB (Transport) and OCDESTATS
	18	Electric power transmission and distribution losses (% of output)*	WDI, World Bank
	19	Energy use (kg of oil equivalent per capita)	WDI, World Bank
	20	Electric power consumption (kWh per capita)	WDI, World Bank
Innovation	21	Exports of high and medium technology (share of total exports)	IDB-CTI calculations based on COMTRADE
	22	Scientific and technical journal articles (per total population)	IDB-RES based on WDI, World Bank
	23	Quality Management Certificates (number of Certificates per billion PPP$ GDP)	The ISO Survey of Management System Standard Certifications (1993-2013) and WEO, IMF

Table A1. Individual Indicators Used for Construction of Sectoral Indicators (continued)

Integration & Trade	24	Foreign direct investment, net inflows (% of GDP)	WDI, World Bank
	25	Hummels-Klenow extensive margin index: markets	IDB-INT calculation based on World Bank and WITS Trade Outcomes Indicators based on UN COMTRADE data
	26	Hummels-Klenow extensive margin index: products	IDB-INT calculation based on World Bank and WITS Trade Outcomes Indicators based on UN COMTRADE data.
	27	Trade openness (% GDP in PPP)	IDB-INT based on DOTS and WEO, IMF
Labor Markets	28	Formal employment ratio: Active contributors to an old age contributory scheme (% of labor force)	IDB-LMK calculations (SIMS). For OCDE, World Bank and ILOSTAT
	29	NEETS youth 15-24 (Labor)*	IDB-LMK calculations (SIMS). For OCDE, https://data.oecd.org/youthinac/youth-not-in-education-or-employment-neet.htm
	30	Unemployment ratio, total (15-64)*	WDI, World Bank
	31	Workers with low education levels as a percentage of total workers (15+)*	IDB-LMK calculations (SIMS). For OCDE, OCDESTATS
Telecommu-nications	32	Internet users (per 100 people)	ITU (International Telecommunications Union)
	33	Mobile lines (per 100 people)	ITU (International Telecommunications Union)
	34	Telephone lines (per 100 people)	ITU (International Telecommunications Union)

*Series is first normalized and then multiplied by -1 to reflect that it has a negative impact on the sector's performance.

Table A2. Distribution of Country-Year GDP per Capita Observations by Cluster

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Bolivia 2000-2010	Bolivia 2011-2012	Argentina 2000-2012	Australia 2000-2012
Honduras 2000-2012	Colombia 2000-2010	Brazil 2000-2012	Austria 2000-2012
Nicaragua 2000-2012	Costa Rica 2000-2005	Chile 2000-2012	Belgium 2000-2012
	Dominican Republic 2000-2009	Colombia 2011-2012	Canada 2000-2012
	Ecuador 2000-2012	Costa Rica 2006-2012	Denmark 2000-2012
	El Salvador 2000-2012	Czech Republic 2000-2012	Finland 2000-2012
	Guatemala 2000-2012	Dominican Republic 2010-2012	France 2000-2012
	Jamaica 2000-2012	Estonia 2000-2012	Germany 2000-2012
	Panama 2000-2004	Greece 2000-2003; 2011-2012	Greece 2004-2010
	Paraguay 2000-2012	Hungary 2000-2012	Iceland 2000-2012
	Peru 2000-2011	Israel 2000-2009	Ireland 2000-2012
		Korea 2000-2009	Israel 2010-2012
		Mexico 2000-2012	Italy 2000-2012
		Panama 2005-2012	Japan 2000-2012
		Peru 2012	Korea 2010-2012
		Poland 2000-2012	Netherlands 2000-2012
		Portugal 2000-2012	Norway 2000-2012
		Slovak Republic 2000-2012	Slovenia 2007-2008
		Slovenia 2000-2006; 2009-2012	Spain 2000-2012
		Turkey 2000-2012	Sweden 2000-2012
		Uruguay 2000-2012	Switzerland 2000-2012
		Venezuela 2000-2012	United Kingdom 2000-2012
			United States 2000-2012

Table A3. VEC Granger Causality/Block Exogeneity Tests

Dependent Variable: Aggregate Indicator			
Excluded Variable	Chi-squared	Differences	Probability
Log GDP p/c, PPP Adjusted	5.115164	2	0.0775

Dependent Variable: Log GDP p/c, PPP Adjusted			
Excluded Variable	Chi-squared	Differences	Probability
Aggregate Indicator	6.637232	2	0.0362
Observations	256	256	256
Countries	47	47	47

Note: The null hypothesis of the Granger Causality Test is that the excluded variable does not Granger cause the Dependent Variable.

Table A4. Results of Generalized Ordered Probit with Lagged VIX (Restricted Coefficient)

	(1) Cluster 1	(2) Cluster 2	(3) Cluster 3
Capital Markets	0.304	-0.233	1.725***
	(0.782)	(0.452)	(0.627)
Education	1.155**	-0.046	-0.727
	(0.533)	(0.287)	(0.468)
Health	0.738**	0.738**	0.738**
	(0.320)	(0.320)	(0.320)
Infrastructure	0.541	-0.388	4.143***
	(0.864)	(0.362)	(1.055)
Innovation	3.388	1.578	-0.313
	(2.099)	(0.978)	(0.576)
Integration & Trade	1.177	1.106**	-0.415
	(1.181)	(0.554)	(0.271)
Labor	-0.716	0.904**	-0.669
	(1.460)	(0.381)	(0.463)
Telecommunications	0.098	0.098	0.098
	(0.303)	(0.303)	(0.303)
Lag_VIX	-0.026***	-0.026***	-0.026***
	(0.009)	(0.009)	(0.009)
Observations	396	396	396
Country Cluster	47	47	47

Note: Coefficient standard deviations are estimated using clustered errors at the country level.
***Significant at the 1% level, **Significant at the 5% level.

Table A5. Summary Statistics of Coefficient Distributions

		Percentage of observations that fall inside a one standard deviation window	Percentage of observations that match the significance of the main regression coefficient *	Excess Kurtosis	Excess Skewness-Adjusted Kurtosis
Cluster 1	Capital Markets	91.72	100.00	134.79	134.45
	Education	81.64	99.80	30.73	27.16
	Health	92.52	99.44	233.04	157.07
	Infrastructure	85.68	100.00	59.74	52.92
	Innovation	92.26	98.98	208.03	141.68
	Integration and	85.70	100.00	96.35	68.37
	Labor	92.04	100.00	179.58	124.42
	Telecommunicat	97.46	99.62	245.90	161.19
	VIX	71.20	100.00	7.40	6.93
Cluster 2	Capital Markets	78.18	100.00	22.90	21.55
	Education	78.04	100.00	22.51	19.23
	Health	75.50	99.44	24.15	23.38
	Infrastructure	83.00	100.00	88.59	70.49
	Innovation	78.44	100.00	17.25	16.83
	Integration and	78.12	100.00	11.60	9.31
	Labor	78.62	100.00	29.26	22.23
	Telecommunicat	74.32	100.00	13.48	13.37
	VIX	71.20	100.00	7.40	6.93
Cluster 3	Capital Markets	83.62	100.00	27.13	17.57
	Education	85.44	100.00	70.31	56.09
	Health	96.88	99.82	246.68	161.59
	Infrastructure	88.84	100.00	78.47	50.32
	Innovation	85.20	100.00	57.30	40.33
	Integration and	83.54	100.00	52.01	48.92
	Labor	86.36	100.00	52.31	37.28
	Telecommunicat	93.08	100.00	221.87	146.55
	VIX	71.20	100.00	7.40	6.93
Average		83.70	99.89	83.19	60.85

Note: Excess kurtosis is relative to that of a normal distribution (which has a value of 3). Skewness-adjusted kurtosis is done following Blest (2003).

* Percentage of estimated coefficients generated randomly by changing the sample that coincide with that of the original estimation in terms of being significant (or not significant) at the 5% level.