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Exploring the Relationship between Foreign Direct Investment and Mobile Technology in Africa: An Application of Directed Acyclic Graphs

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The adoption of wireless mobile technology is increasingly gaining popularity globally and most especially in Africa. This advancement is propelled not only as a social networking device, but as a business operating tool. We investigate whether the penetration of wireless technology has a directed effect on foreign direct investment (FDI) in 47 African emerging markets for three time periods – 2001, 2004 and 2006. We estimate Directed Acyclic Graphs (DAGs), using the Partial Correlation (PC) and Greedy Equivalence Search (GES) algorithms to ascertain the direction of association between the penetration of wireless mobile technology and the level of FDI inflows. Our study indicates a significant successive growth in mobile technology in African economies and also suggests that mobile cell phone growth in Africa is an antecedent of FDI rather than a consequence since the DAG estimates a directional flow from mobile wireless technology to FDI across both the PC and GES algorithms.

Keywords: *Wireless mobile technology, Foreign Direct Investment, Africa, Directed Acyclic Graphs, Tetrad IV*

Introduction

Once considered a luxury, mobile phones are fast becoming tools of necessity. They rely on a powerful technology that drives economic and social forces from rapid changes in capabilities and price to performance (Kumar and Zahn 2003). A prior study by LaFraniere (2005) on mobile phone technology in the African Market indicates that Africa is the world's fastest-growing cell phone market; the number of mobile subscribers jumped from 7.5 million in 1999 to 76.8 million in 2004, an average annual increase of 58 percent. By early 2008, Africa had surpassed North America in terms of the number of mobile subscribers with more than 280 million subscribers (Wireless Federation Homepage, 2008). Thus, mobile users in Africa have experienced a revolutionary change, from communicating by beating drums, having to leave work and travel for days, or spending a lot of money just to pass on a message to communicating instantly via text messages and cell phone calls. A related study also noted that the number of subscribers in Nigeria, Africa's most populous country, grew from about 4 million in 2003 to about 113 million in 2008 (Nigerian Communications Commission Industry Statistics, 2008).

Several economic studies suggest that African economies are largely left behind developmentally when it comes to foreign direct investment (FDI) flows (Morisset, 1992; UNCTAD, 1999; Asiedu, 2006). Other studies show that because of negative compounding factors, only three African economies – South Africa, Nigeria and Angola at one point accounted for 65 per cent of total FDI flows to Africa and about two-third of the sub-continent's Gross Domestic Product (GDP) (World Bank, 2004b; Aseidu, 2006). The benefits of FDI cannot be overemphasized as FDI brings capital, technology, jobs, links to the global economy, opportunities for external resources that contribute to economic development, and facilitates e-business (Sachs, 2007; Kim et al, 2004).

The significant demand and growth in wireless mobile phone technology in Africa are depicted in Figures 1 and 2 respectively. Figure 1 exemplifies the aggregate geometric growth in mobile phone subscription density from 2001 to 2006, while Figure 2 shows the same subscription growth by region over the same period where the North and South regions appear to have done much better than other regions.

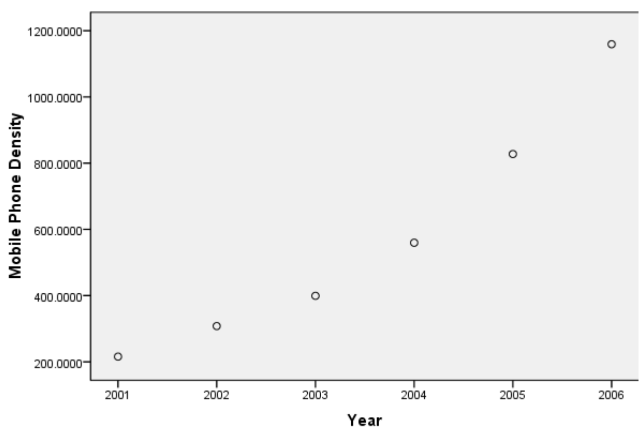


Figure 1. Mobile Phone Subscriptions (per 10,000)

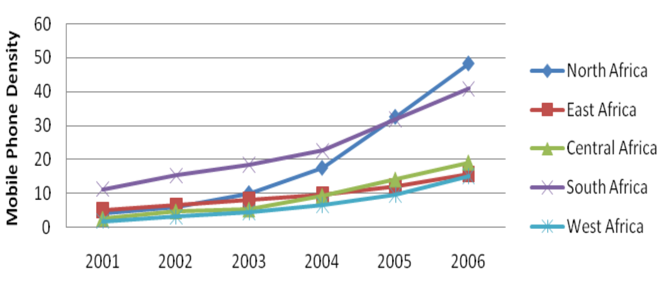


Figure 2. Mobile Phone Density by Region (per 100)

Using Directed Acyclic Graphs (DAGs), this paper explores whether FDI is an antecedent or consequence to mobile phone technology growth in Africa's emerging markets especially following the UN's declaration of the 2000 MDGs. In evaluating the above objective, this study considers the following research question: what is the direction of association between mobile phone growth and other economic, demographic and risk factors such as FDI, GDP per Capita, Population density and Risk ratings in Africa? Specifically, is wireless mobile technology an antecedent or consequence of FDI? This study will be of interest to researchers in assessing how/whether the declaration made by the UN towards providing technological development to African countries is likely to have had an economic impact. Further, the study contributes an innovative application of the DAG methodology to a case study on FDI and wireless mobile technology in Africa.

Directed Acyclic Graphs as a technique have been applied in a number of related studies. Haughton et al. (2006) emphasized that DAG modeling is a powerful analytic tool to consider in conjunction with, or in place of, path analysis, structural equation modeling, and other statistical techniques. For example, Eshghi et al. (2007) investigated the determinants of customer loyalty among wireless service providers by applying DAG to derive causal models under restrictive conditions. Similarly, Bessler (2003) and Bryant et al. (2009) used DAG to sort-out causal patterns among set of measures deemed relevant to the incidence of world poverty and disproving causal relationships using observational data, respectively. Further details about the DAG methodology can be found in Haughton and Haughton (2011), chapter 5. In this paper, we investigate the directional relationship between FDI and mobile technology in Africa using DAGs.

The remainder of the paper is organized as follows. Section two describes the directed acyclic graph methodology used in this study. Sections three and four present the results and discuss the implications and conclusions, respectively.

Methodology

Directed Acyclic Graphs

A directed acyclic graph is a picture representing the directional links among a set of variables. Consider a set of variables, X, Y and Z. A directional fork where X is an antecedent of both Y and Z can be shown as $Y \leftarrow X \rightarrow Z$. A graph is an ordered triple <V, M, E> where V is a non-empty set of vertices (variables), M is a non-empty set of marks (symbols attached to the end of undirected edges) and E is a set of ordered pairs where each member of E is called an edge (Bessler, 2003; Zhang et al., 2006).

Vertices linked by an edge are considered adjacent. Given a set of vertices, {mobile Phone (M.P), FDI, GDP}, an undirected graph will have undirected edges, i.e. M.P – FDI while a directed graph contains only directed edges, i.e. FDI → GDP. A directed acyclic graph is different from a directed graph in that it has no directed cyclic paths. That is, a directed acyclic graph has no path that leads away from a variable only to return to that same variable. This paper applies the concept of directed acyclic graphs to wireless technology growth and FDI in African countries.

Directed Acyclic Graphs Methodology

Directed Acyclic Graphs are directional pictures where the variables are represented by nodes and the edges represent the conditional dependence among the variables (Haughton et al 2006, see also Haughton and Haughton 2011, chapter 5). A directed edge from x to y indicates that x is a parent of y. If $V_1 \ldots V_n$ is the set of variables and *parent*(V_i) represents the set of parents of variable Vi, then a DAG represents a joint distribution f if the following decomposition holds:

$$f(V_1 ... V_n) = \prod_{i=1}^{n} f(V_i \mid parent(V_i))$$

where on the left hand side f is the probability distribution function of variables $V_1 \ldots V_n$ and on the right side, each term represents the conditional probability distribution function of V_i given its parents (Bessler, 2003; Esghi et al, 2007; Haughton et al, 2006; Zhang et al, 2006). By a theorem due to Pearl (Pearl, 2000), the decomposition implies that each variable is independent of its non-descendants given its parents. Thorough introductions and discussions of this methodology and case studies can be found in a variety of papers (Pearl, 2000; Bessler, 2003; Haughton et al, 2006; see also Haughton and Haughton, 2011, chapter 5).

Directed Acyclic Graphs using TETRAD

The software package TETRAD IV (Tetrad Project Homepage, 2012) is used in this paper to construct DAGs from data. Tetrad IV provides a number of different search algorithms that are guaranteed to converge to correct information about the true structure in the data provided the data satisfy some assumptions such as normality (Tetrad Project Homepage, 2012). The program is given no prior knowledge or hypothesis about which variables are causes or which are effects, thus the results are driven by the structure of the data. TETRAD IV can be accessed at no cost from http://www.phil.cmu.edu/projects/tetrad.

TETRAD contains a suite of different search algorithms such as the PC (Partial Correlation), GES (Greedy Equivalence Search) and FCI (Fast Causal Inference) algorithms. For the purpose of our study, we use the PC and GES algorithms. The PC algorithm begins by creating a complete undirected graph where each variable represents a vertex and undirected edges connect all the variables. Edges between the variables are removed on the basis of significance tests of zero correlation or zero conditional correlation (Haughton et al, 2006; Zhang et al, 2006, Haughton and Haughton, 2011, chapter 5). The remaining undirected edges are now "directed" by taking each triplet x, y, z where both pairs (x, y) and (y, z) are linked but (x, z) is not linked. If y does not appear in any set which, when conditioned on, makes x and z independent, then the triplet x, y, z is oriented as x→ y ←z. which makes y a collider. After identifying all colliders, the algorithm proceeds by looking at the directed edge between x and y, i.e. x→y. If y and z are linked and x and z are not linked, and if there is no arrowhead at y, then (y, x) is oriented as y→z (Esghi et al, 2007, Haughton and Haughton 2011, chapter 5). The algorithm is discussed in detail in Spirtes et al. (2000). Studies have identified that the PC algorithm may make mistakes of edge exclusion or inclusion and edge direction especially with small sample sizes (Demiralp and Hoover, 2003; Spirtes et al, 2000; Zhang et al, 2006). However, Sprites et al (2000) suggest that higher significance levels may improve performance for small sample sizes.

The GES algorithm is a two-phase search algorithm that uses a different strategy than the PC algorithm but arrives at the same results as PC under similar conditions (TETRAD Tutorial). The first phase of the GES algorithm starts with a completely disconnected graph without any edges between the variables. The directed edge that most improves the Model selection criterion BIC is then added to the graph. An iterative process keeps adding directed edges to the graph in this way. The direction of some previous edges might be changed as this process continues, until no additional edge improves the BIC score. The second phase involves the algorithm working backwards. Edges are removed one at a time to see if their removal improves the BIC score. Again this continues until there are no more improvements (TETRAD Tutorial). Chickering (2002) provides extensive details about the GES algorithm. As mentioned earlier, the strategy behind the GES algorithm is different from that behind the PC algorithm. Zhang et al (2006) propose that researchers can have a higher confidence in edges or directions that are robust across both algorithms than edges or directions that change under the different search algorithms.

Data

The indicators included in the analysis are guided by the choice of variables in Chinn and Fairlie (2007) and Deichmann et al (2007). Our final analysis included 47 African countries and 5 indicator variables for three time periods 2001, 2004 and 2006. We estimate a DAG for each time period in order to see how/whether the direction of effect changes over time. The variables in the dataset are arranged into the following four groups: Digital development, Economic, Demographic, and Risk. These groupings are commonly agreed factors for explaining the differences across regions in digital growth (Deichmann et al, 2007). For the purposes of this paper, the digital development group consists of one variable – the number of mobile subscribers per 100 people. This variable represents the growth in the adoption of mobile phone technology across African countries.

The economic group includes two economic variables. The Gross Domestic Product (GDP) per capita is the basic measure of a country's overall economic output divided by mid-year population. The GDP measures the total market value of all final goods and services produced in a country in a given year, equal to total consumer, investment and government spending, plus the value of exports, minus the value of imports (World Bank 2012). The second variable in this group is the Foreign Direct Investment Net Inflows as a percentage of GDP. It measures the value of net inflows of FDI at the country-level, in million US dollars (current) as a percentage of the GDP. FDI is defined as the net inflows of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor. It is the sum of equity capital, reinvestment of earnings, other long-term capital, and short term capital, as shown in the balance of payments (World Bank, 2012).

The fourth group consists of a demographic variable – population density. This variable is relevant to our study as it provides a context for how the population density of a country influences the other variables in our study such as the adoption of mobile phone technology, FDI and GDP per capita.

The last group is the risk group. We use the country risk rating from IHS Global Insight (2012) which incorporates economic, political, legal, tax, operational, and security risk ratings. We believe the IHS risk rating presents a comprehensive picture of the quality of conditions and level of stability in each country. We hypothesize that this would have an effect on digital and economic development or vice versa. Table 1 contains a list of indicator variables used in the study.

Table 1. Indicator Variables

Indicator*	Description	Source	Group
Mobile	Number of mobile subscribers per 100 people	World Bank – WDI	Digital Development
GDP	GDP Per Capita	World Bank – WDI	Economic
FDI	Foreign Direct Investment (net inflows)	World Bank – WDI	Economic
Population Density	Percentage of population age 15-64	World Bank – WDI	Demographic
Risk	Country Risk Rating	IHS Global Insight	Risk

*All variables were transformed with the natural logarithm function

Analysis and Results

We excluded from our analysis African countries with missing data, leaving us with 47 African countries. Some of the search algorithms in TETRAD work best with approximately normal data, so we first examined the distribution of our data. This is easily done in TETRAD by clicking on the tools menu at the top of the data wrapper and clicking Histogram (Figure 3). We transformed each of our variables with the natural logarithm to ensure a less skewed distribution, including in the case of the FDI variable which is close to non-normally distributed (Figures 3 and 4). We also look at the normality tests in TETRAD by clicking on the tools menu and selecting tests. TETRAD provides results for the Kolmogorov Smirnov and Anderson Darling Tests at various significance levels (Figure 4).

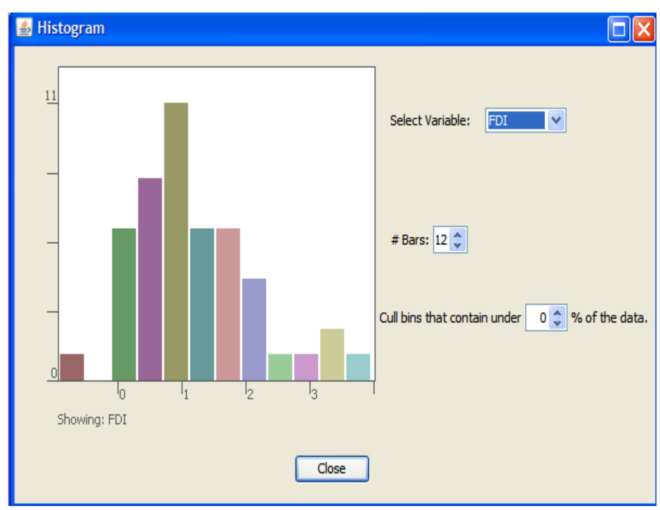


Figure 3. Histogram Distribution

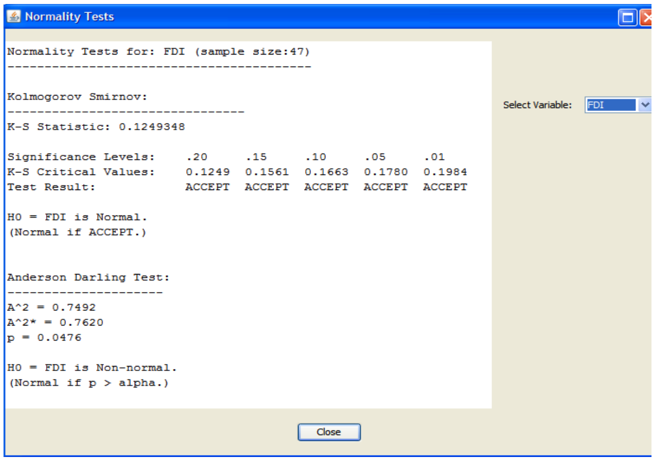


Figure 4. Normality Tests

We begin our analysis by using PC and GES algorithms in TETRAD IV on the 2001 dataset. Zhang et al (2006) propose that higher significance levels may improve performance at small sample sizes so given our sample size of 47 countries. We analyze results for the PC algorithm at the 30% significance level. This is the lowest significance level that produces an unambiguous directed ordering in our analysis. The graph that is produced using the PC search algorithm is the algorithm's estimate of the dependency structure that generated the data (TETRAD Tutorial). It is important to remember that the resulting DAG that is produced is data-driven without a priori knowledge of the directed relationships among the five variables.

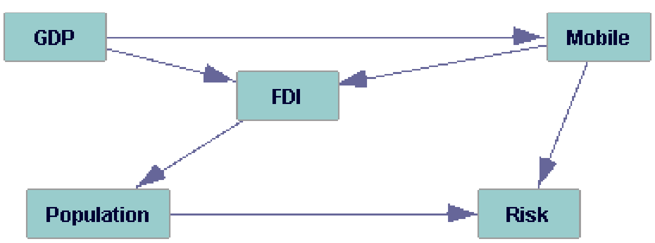


Figure 5. DAG Pattern by PC algorithm 2001

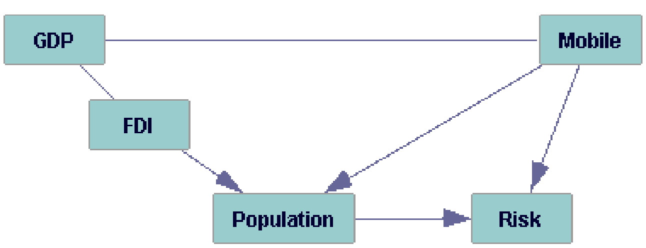


Figure 6. DAG Pattern by GES algorithm 2001

The PC algorithm at the 30% significance level produces a graph with all six directed edges. There is a directed effect from GDP per capita to mobile phone subscriptions per capita and FDI. Mobile phone subscription also has a directed effect on FDI and the Risk rating of the country. FDI has a directed effect on the population density which in turn has a directed effect on risk.

The GES algorithm does not allow the user to specify different significance levels. The algorithm presents one graph with four directed edges and two undirected edges. In this graph the two undirected edges are among GDP, mobile and FDI. The directed edges show a flow from mobile to population density and risk. There is also a flow from FDI to population density, which in turn has a directed effect on risk. The directed edges from mobile to risk, FDI to population density and population density to risk are consistent with results from the PC algorithm.

Model statistics are also provided in TETRAD for the PC and GES graphs. We are also able to obtain a maximum likelihood estimate of the parameter (edges) values with corresponding standard errors, t statistics and p values for the PC graph (Figures 7, 8 and 9). All the variables have positive edge coefficients except for mobile to risk which has a negative coefficient of -0.0698 (Table 2), which is sensible given that higher risks correspond to lower values of the variable RISK. The directed edge from GDP to mobile has an edge coefficient of 0.8634 while the edge coefficient from mobile to FDI is 0.1892. The PC graph has a BIC score of -3.56 and a p value of 0.0186. The GES graph has a BIC score of -8.4779 and a p value of 0.14. Correlation and Covariance matrices can also be obtained from TETRAD IV. All the variables are highly correlated with each other with correlations above 0.9 (Table 3). The GES algorithm seems to provide a better fit.

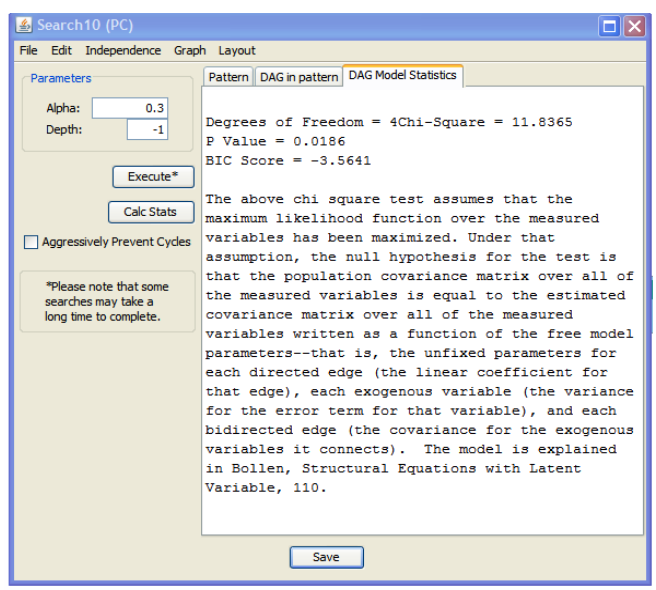


Figure 7. Model Statistics

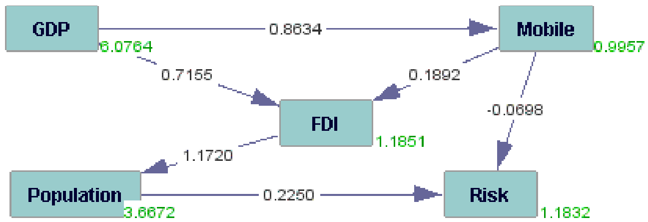
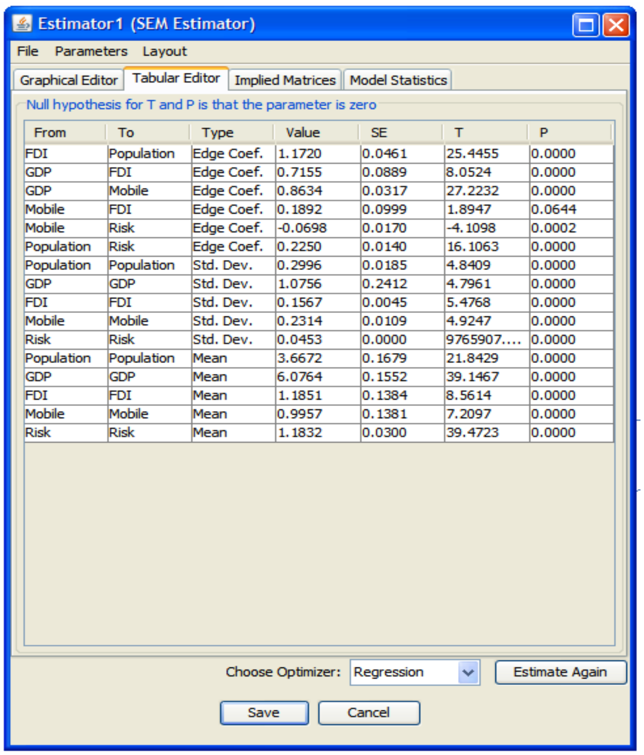


Figure 8. PC DAG with edge coefficients - 2001



From	To	Type	Value	SE	T	P
FDI	Population	Edge Coef.	1.1720	0.0461	25.4455	0.0000
GDP	FDI	Edge Coef.	0.7155	0.0889	8.0524	0.0000
GDP	Mobile	Edge Coef.	0.8634	0.0317	27.2232	0.0000
Mobile	FDI	Edge Coef.	0.1892	0.0999	1.8947	0.0644
Mobile	Risk	Edge Coef.	-0.0698	0.0170	-4.1098	0.0002
Population	Risk	Edge Coef.	0.2250	0.0140	16.1063	0.0000
Population	Population	Std. Dev.	0.2996	0.0185	4.8409	0.0000
GDP	GDP	Std. Dev.	1.0756	0.2412	4.7961	0.0000
FDI	FDI	Std. Dev.	0.1567	0.0045	5.4768	0.0000
Mobile	Mobile	Std. Dev.	0.2314	0.0109	4.9247	0.0000
Risk	Risk	Std. Dev.	0.0453	0.0000	9765907....	0.0000
Population	Population	Mean	3.6672	0.1679	21.8429	0.0000
GDP	GDP	Mean	6.0764	0.1552	39.1467	0.0000
FDI	FDI	Mean	1.1851	0.1384	8.5614	0.0000
Mobile	Mobile	Mean	0.9957	0.1381	7.2097	0.0000
Risk	Risk	Mean	1.1832	0.0300	39.4723	0.0000

Figure 9. Model Statistics

Table 2. Edge Statistics 2001

From	To	Edge Coefficient	Standard Error	P-value
FDI	Population	1.1720	0.0461	0.0000
GDP	FDI	0.7155	0.0889	0.0000
GDP	Mobile	0.8634	0.0317	0.0000
Mobile	FDI	0.1892	0.0999	0.0644
Mobile	Risk	-0.0698	0.0170	0.0002

Table 3. Correlation Matrix 2001

	Population	GDP	FDI	Mobile	Risk
Population	1.0000				
GDP	0.9523	1.0000			
FDI	0.9663	0.9855	1.000		
Mobile	0.9347	0.9703	0.9673	1.0000	
Risk	0.9686	0.8963	0.9151	0.8643	1.0000

PC and GES Analyses - 2004 Dataset

We analyze results for the 2004 dataset using the PC algorithm at the 30% significance level and the GES algorithm. The DAG pattern by PC gives a graph with all six directed edges. GDP has directed effects on FDI, mobile phone subscriptions per 100 people and population density. Mobile phone subscriptions have a directed effect on FDI. Risk has a directed effect on population density and this result is opposite to what we saw earlier in the 2001 graph. Population density also has a directed effect on mobile phone subscriptions.

The GES algorithm produces a graph with four directed edges and two undirected edges. GDP has a directed effect on FDI, while mobile phone subscriptions have directed effects on FDI and GDP. Population density and risk have directed effects on GDP, while the undirected effects are among population density, mobile phone subscriptions and risk. The directed effects from GDP to FDI and mobile to FDI are consistent across both algorithms.

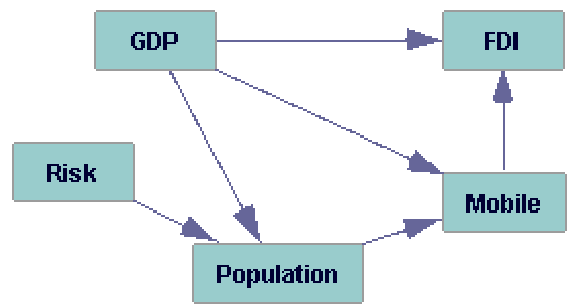


Figure 10. DAG Pattern by PC algorithm 2004

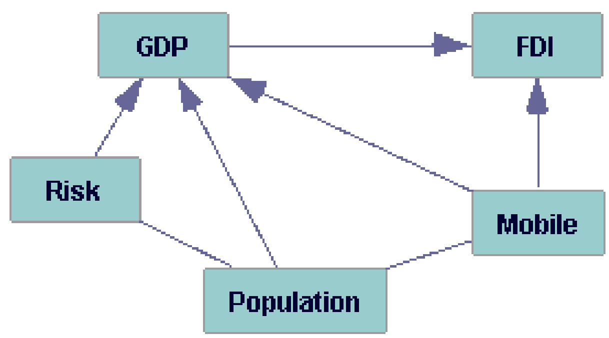


Figure 11. DAG Pattern by GES algorithm 2004

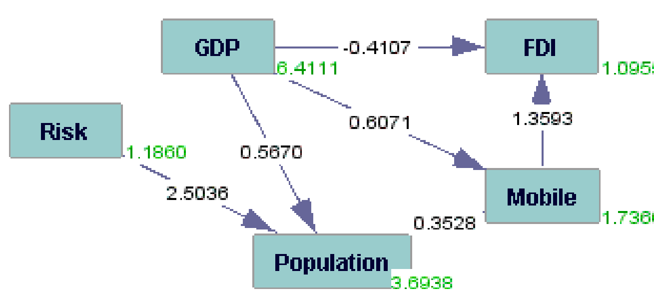


Figure 12. PC DAG with edge coefficients 2004

The correlation matrix for the 2004 dataset indicates that mobile phone subscriptions are highly correlated with FDI and GDP with respective correlations of 0.9435 and 0.9624. Interestingly, the risk rating has low correlations with GDP, FDI and Mobile phone subscriptions at 0.0000, 0.2640 and 0.1828 respectively. All variables for the PC graph have positive edge coefficients except for the directed edge from GDP to FDI in 2004 which has a negative coefficient of -0.4107. Mobile to FDI has an edge coefficient of 1.3593 and this is much higher than the edge coefficient for the 2001 dataset. This indicates a much stronger relationship between mobile phone subscriptions and FDI in 2004 than was obtained in 2001. The PC graph has a BIC score of 68.8923 and a p value of 0.000, while the GES graph has a BIC score of -11.0869 and p value of 0.9268. GES clearly provides a better fit.

Table 4. Edge Statistics 2004

From	To	Edge Coefficient	Standard Error	P-value
GDP	FDI	-0.4107	0.1867	0.0329
GDP	Population	0.5670	0.0533	0.0000
GDP	Mobile	0.6071	0.1000	0.0000
Mobile	FDI	1.3593	0.1937	0.0644
Population	Mobile	0.3528	0.1009	0.0011
Risk	Population	2.5036	0.3071	0.0000

Table 5. Correlation Matrix 2004

	Population	GDP	FDI	Mobile	Risk
Population	1.0000				
GDP	0.7769	1.0000			
FDI	0.8515	0.8697	1.000		
Mobile	0.8694	0.9624	0.9435	1.0000	
Risk	0.5953	0.0000	0.2640	0.1828	1.0000

PC and GES Analyses - 2006 Dataset

The PC algorithm for the 2006 dataset yields a DAG graph with six directed edges. Risk has a directed effect on FDI, mobile phone subscriptions and population density. Mobile phone subscriptions have a directed effect on FDI, and FDI in turn has a directed effect on GDP. The directed effect from mobile phone subscriptions to FDI in 2006 is consistent with the result from the 2004 dataset. On the other hand, the direction of effect from GDP to FDI that is shown in the two earlier periods has now changed in 2006. Risk rating also has an effect on the FDI net inflows for African countries unlike in the earlier time periods where there was no direct relationship.

GES yields a DAG with four directed edges and two undirected edges. Risk has a directed effect on FDI. FDI in turn has a directed effect on GDP and mobile phone subscriptions and population density have directed effects on FDI. The undirected edges are between population density, risk rating and mobile phone subscriptions. Consistent across both algorithms are the directed effects from Risk to FDI, FDI to GDP, mobile subscriptions to FDI and population density to FDI. As for the previous years 2001 and 2004, GES provides a better fit.

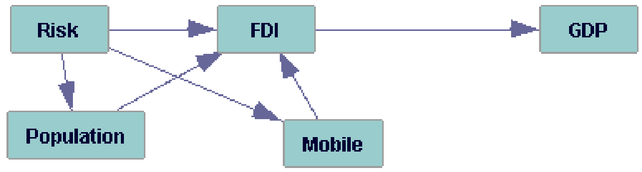


Figure 13. DAG Pattern by PC algorithm 2006

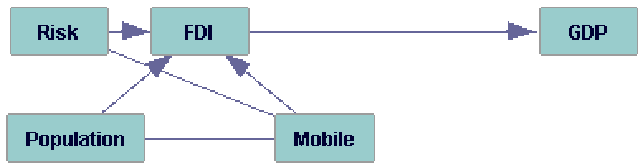


Figure 14. DAG Pattern by GES algorithm 2006

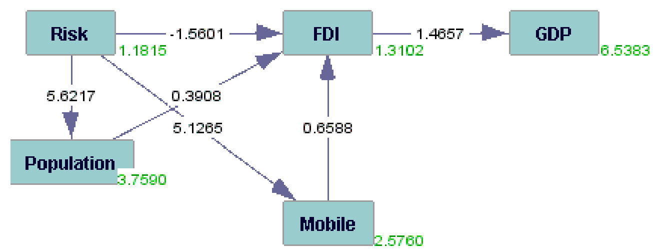


Figure 15. PC DAG with edge coefficients 2006

Table 6. Edge Statistics 2006

From	To	Edge Coefficient	Standard Error	P-value
FDI	GDP	1.4657	0.0572	0.0000
Mobile	FDI	0.6588	0.0936	0.0000
Population	FDI	0.3908	0.0845	0.0000
Risk	Mobile	5.1265	0.2140	0.0000
Risk	Population	5.6217	0.2371	0.0000
Risk	FDI	1.5601	0.2989	0.0000

Table 7. Correlation Matrix 2006

	Population	GDP	FDI	Mobile	Risk
Population	1.0000				
GDP	0.9230	1.0000			
FDI	0.9573	0.9642	1.000		
Mobile	0.9236	0.9442	0.9793	1.0000	
Risk	0.9606	0.9188	0.9529	0.9614	1.0000

The correlation matrix for 2006 PC graph indicates that all the variables are highly correlated with correlations above 0.9. Mobile and FDI have the highest correlations at 0.9793. All edges have positive coefficients with p values of 0.0000. Also, mobile to FDI has a coefficient of 0.6588, while FDI to GDP has a coefficient of 1.4657. The PC graph has a BIC score of 37.5454 and p value of

0.000, while the GES graph has a BIC score of -10.6797 and p value of 0.3079.

Conclusion

Using data from three time periods (2001, 2004 and 2006), we investigate the direction of effect between mobile phone growth in Africa and FDI using Directed Acyclic Graphs. We find that in all three time periods, there is a directed effect from mobile phone growth to FDI. This effect is consistent across both the PC and GES algorithms in 2004 and 2006 and this allows us to have a degree of confidence in the results. This implies that as mobile phone adoption increases across Africa, there is a potential for simultaneous increase in Foreign Direct Investment inflows to Africa. As a caveat, we do not attempt to suggest that TETRAD infers causality between growth in mobile phone adoption and FDI because such an inference, as explained for example in Eshghi et al (2007) and Haughton and Haughton (2011, chapter 5) would require a very strong assumption of "causal sufficiency". TETRAD has enabled us to not only deduce the existence of a directional link from mobile phone to FDI, but also identify pairs of variables that are dependent on each other, given all the other variables in the set of variables. The African experience with the recent explosion in mobile phone adoption and use is quite unique relative to other regions. An interesting topic for future research would be to explore the directional links between FDI and mobile phone growth in other regions such as Asia, Latin Americas and the Caribbean.

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