Financial Development and The Diffusion of Technologies under Uncertainty in Africa

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Abstract

Using novel measures of technology diffusion and adoption developed by Comin and Hobijn (2012), we examine the role of finance in the *timing* of adoption and the *diffusion* of thirteen sectoral technologies in 44 Sub-Saharan Africa countries. These technologies cover sectors such as agriculture, communication and information technology, industry, and transport. The results show that financial development enhances the *timing* and *diffusion* of technologies both directly, and indirectly, through reducing the risk associated with new technologies. However, the results differ across technologies, with the information and communication technologies showing more responsiveness to changes in financial development. There is also evidence to suggest that, subject to the level of economic development, some technologies diffusion faster, while others diffuse slower. The latter result implies that some sector-specific technologies may diffuse quicker in less developed economies, and thus economic theory needs to be extended to account for this technology-specific feature.

JEL Classification: E44, G21, O30, O33

Key Words: Financial Depth, Technology Diffusion, Timing of Adoption, Economic Development, Macroeconomic Volatility, Institutions, Dynamic panels, GMM

1 Introduction

The role of finance in economic development has been subject to extensive theoretical and empirical analysis since Schumpeter (1911) suggested the potential role of a well-developed financial system in enhancing productivity by accelerating the reallocation of resources in the process of 'creative destruction' (see

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for example Goldsmith, 1969; Lucas, 1988; Greenwood and Jovanovic, 1990; King and Levine, 1993; Obstfeld, 1994; Levine, 1997 and Levine, 2003), albeit with mixed findings.[1] While some literature support the idea that finance enhances growth and development (see King and Levine, 1993; Levine, 2003), some authors cast doubt, arguing that financial market development is not a pre-requisite for growth, but an endogenous outcome of growth and development (see Robinson, 1952; Lucas, 1988). Yet another strand of literature argues that there is bidirectional causality between financial development and economic growth (see Greenwood and Jovanovic, 1990; Khan, 1999).

In light of this mixed literature, there has been increased recognition that the research should focus on the channels through which financial development influences growth and development. The idea is that the immediate impact of financial development may not be immediately reflected in aggregate growth and development data, but in other intermediate variables that have the potential to strengthen the economy's capacity for future growth. At the theoretical level, this literature emphasizes the role of finance in promoting growth by enhancing better insurance against risk thereby facilitating the investment high return projects (see for example Greenwood and Jovanovic,1990; Saint-Paul, 1993; Obstfeld, 1994), mobilizing savings and facilitating efficient allocation of resources (see for example King and Levine, 1993; Greenwood, 2010), reducing asymmetric and agency costs, and enhancing innovation (see Leland and Pyle, 1977; Fama, 1980; Diamond, 1984; Aghion *et al.*, 2004). At the empirical level, studies such as Galindo *et al.* (2007), Abiad *et al.* (2008), Chinzara, *et al.* (2012) support the role of finance in efficient allocation of resources. Hoshi *et* al. (1989) provide evidence based on the Japanese banking system that bank motoring reduces asymmetric information and agency costs. Sorensen, *et al.* (2006), Artis and Hoffman (2006), Giannone and Reichlin (2006) document cross-country evidence that financial liberation enhances risk sharing.

Within the broader empirical literature that focuses on the channels through which finance affects growth, an emerging, but relatively limited strand examines whether finance matters for the adoption and diffusion of new technologies. Tadesse (2013), Zigorchev *et al.* (2011), Ilyina and Samaniego (2008), Yarley (2008) are examples such empirical studies. There are a number of channels through which financial factors can affect technology adoption and diffusion. Firstly, by reducing the risk associated with new technologies, financial markets may speed up the adoption of new technologies. Indeed a number of theoretical and empirical studies show that risk delays the adoption and diffusion productive technologies (see Tsur, *et al.*, 1990; Love and Buccola, 1991, Saha, *et al.*, 1994; Dercon and Christiaensen, 2011; Chinzara and Lahiri, 2012). Secondly, because small firms are more financially constrained than large firms, the latter firms may adopt new technologies quicker than the former firms (Stoneman, 2001a). Stoneman (2001b) provides evidence that larger firms adopt technologies faster than smaller firms. Thirdly, differences in complexities of technologies imply that their costs, and thus their financing needs are different (Stoneman, 2001a).

[1] Levine (2002) provides an extensive review of this literature.

Davies (1979) documents evidence that there are differences in the adoption of simple and complex technologies. Fourthly, cost of financing may differ because of cross-country differences in financial market completeness, tax regimes, and institutions (Stoneman, 2001a). Zigorchev *et al.* (2011) provide evidence that financial development explains differences in adoption of telecommunication technology across eight Central and Eastern European countries.

The current study contributes to the extant literature by empirically examining two of the channels highlighted above: (i) whether cross-country differences in financial development account for the differences in technology adoption and diffusion (ii) whether the financial development influence the timing of adoption, and the diffusion of technologies by reducing risk. In so doing, the study also contributes by examining whether financial development plays a role in the diversity of growth and inequality experiences across countries, an overarching issue of concern in the larger literature on economic growth and development. Indeed, the role of technological innovation and diffusion in explaining the cross-countries differences in per capita incomes has been emphasized in many studies (see for example, Lucas, 1993; Barro and Sala-i-Martin, 1995; Aghion and Howitt, 1998). As such, if financial development influences cross-country differences in technology diffusion and adoption, it qualifies as a potential explanation for the diversity in growth and inequality patterns.

Our focus on cross-country macro-level effects of financial development on technology adoption and diffusion is related to some of the studies listed above, particularly that of Zigorchev *et al.* (2011). However, the contribution of this study to the extant literature is threefold. Firstly, unlike the studies reviewed above we also examine the role of finance in the timing of technology adoption decisions, which has not been addressed in previous studies. Related studies have addressed the role of factors such as adoption costs, uncertainty, market structure, etc (see Hoppe, 2002; Milliou and Petrakis, 2011; Lahiri and Ratnasiri, 2013; Chinzara and Lahiri, 2012, and references therein).

Secondly, our coverage of technologies is more comprehensive. We explore more than ten technologies covering five main sectors of the economy: the agricultural sector, communication sector, energy sector, information and technology sector, and transport sector. Thirdly, the approach we use to measure technology diffusion is distinct from that used by the above-mentioned studies. We use measures of diffusion and timing recently developed by Comin and Mestieri (2013) and Comin, *et al.* (2006, 2008).

The focus on sub Saharan Africa is also an important contribution as the role of finance in technology adoption in this region has not been explored. The existing studies on technology adoption in SSA focus on the role of factors such as costs, risk, weather patterns on the adoption of technologies (see Dercon 2002, Dercon and Christiaensen, 2011; Giné and Yang, 2008). The majority of these studies are country-specific and their empirical analysis is often based on survey data collected from adopters and potential adopters of sector-specific technologies, particularly those for the agricultural sector (see Dercon 2002, Dercon and Christiaensen, 2011). The focus on agriculture might be because most SSA countries are highly dependent on the primary sector. However, over the past few years, there has been concerted effort by African governments, policy makers and think-tanks to find ways of structurally transforming and diversifying the African economy.

Moreover, African countries have recently adopted a common position that advocates structural transformation, inclusive industrialization and economic diversification as the key economic development themes of the post-2015 development agenda.[2] The adoption of productive technologies in the key sectors is by no doubt one of the channels through which these economic themes will be achieved. Furthermore, in light of recent reduction of foreign funding, particularly aid from OECD countries, the Common African Position (CAP) advocates for financing industrialization using financial resources mobilized from domestic sources. The cost of domestic funds will depend on the depth and quality of domestic capital markets. Therefore the current study is also important in the sense that it informs on the role of domestic financial markets in financing inclusive industrialization in Africa.

The empirical results of this study show that financial development directly enhances the early adoption and quick diffusion of technologies. Furthermore, the results show that financial development indirectly enhances technology adoption through minimizing the risk associated with these technologies. This finding is consistent to theoretical literature that emphasizes the role of finance in reducing risk (see Greenwood and Jovanovic, 1990; Obstfeld, 1994). Our results are consistent across most of the technologies considered, and are robust to a number of stringent tests. Consistent to Stoneman (2001a) and Zigorchev *et al.* (2011), the results imply that cross-country differences in timing of adoption and diffusion of productivity-enhancing technologies can, in part, be traced to cross-country differences in the level of financial development. The other usual determinants of technology diffusion such as human capital development and institutional quality are also statistically significant.

Consistent with the literature on development, there is also evidence to suggest that the level of economic development has an impact on technology adoption (see Khan and Ravikumar, 2002). However, unlike in the development literature, we are able to uncover a novel finding that the level of economic development has mixed effects on the speed of diffusion of technologies. More specifically, while some technologies diffuse quicker in countries that are above some *threshold* level of GDP per capita, others diffuse slower. This result highlights the need for extending theoretical literature to incorporate these sectoral and technology-specific dimensions.

The remainder of the paper is organised as follows. In Section 2, we develop a theoretical framework with a risk-averse preference structure to synthesize ideas about the role of costs and risk in adoption and diffusion of technologies, and how the presence of finance alters this. In Section3 we discuss the empirical methodology and the data issues. In Section 4 we present and analyze the empirical results. In Section 5 we present the conclusions and policy implications of

[2]This document has been dubbed the 'Common African Position' (CAP), and it outlines the economic, developmental, political and environmental issues African countries priorities after the expiry of the Millennium Development Goals (MDGs) in 2015 (AUC, 2014).

the study. The appendix presents some of the technical details of the theoretical framework developed in Section 2 and results from our empirical analysis.

2 A Theoretical Model of Technology Adoption under Uncertainty and Financial Intermediation

The model employed adopts an overlapping-generations construct that highlights the idea that technological adoption decisions and the costs faced associated with such decisions are faced at every generation. For example, the adoption of high yield varieties (HYVs) is influenced by weather patterns, which change from time to time, thereby requiring different types of learning in every generation. Similarly, modern technologies such as computers, mobile phones, etc. continually change, and so do their inputs (such as software, antivirus, etc.).

The economy consists of N two-period lived overlapping generations of agents whose wealth holdings are heterogeneous. Time is discrete, with $t = 0, 1 , 2, ...$ The initial distribution of wealth is described by $w(.)$.Agents are born with a unit of unskilled labour endowment that can earn them a subsistence wage, $\overline{w}$. Furthermore, an agent born in period t also inherits wealth $w_{it}$from his/her parents in the form of bequests. Therefore the total wealth of an agent at any time $t$is $W_{it} = \overline{w} + w_{it}$. There are two production technologies in the economy. For ease of reference, we label them *Technology A* and *Technology B*. *Technology A* is risk-free and its return is α. The return on *Technology B* is divided into two components and is on average higher than return on *Technology A*. The first component of the return on *Technology B*$\eta > \alpha$ is certain. The second component of the return $\varepsilon_{i,t}$is subject to idiosyncratic uncertainty, and depends on the type of shock that the economy faces. If the economy faces a goods shock, which occurs with the probability p, then $\varepsilon_{i,t} = \varepsilon_{i,h} > 0$. If the economy faces a bad shock, then $\varepsilon_{i,t} = \varepsilon_{i,l} < 0$. We assume that $\varepsilon_{i,l} < \eta$and$\eta + \varepsilon_{i,l} < \alpha$. The economy produces output (Y)using capital (K).

The production functions $F(K)$ assume a simple *"AK"* specification. Specifically the production functions for *Technology A* and *Technology B* are $F(K_t)$ $= AK_t$and $F(K_t) = BK_t$respectively, where A and B are the respective total factor productivities associated with the technologies, where $A<B$. In the context of this model, K represents a composite good embodying both human and physical capital. In this model the technology adoption decision recurs in every period, so that each generation faces a technology adoption decision. An agent's choice of technology depends on the magnitude of resources they inherit from their parents.

The agent does not consume in the first period of his life[3]. The utility of

[3]This type of preference structure is consistent with the idea that 'consumption' consists of household consumption which includes the consumption of the children. The agent therefore 'consumes' part of the consumption of his parents in the first period of his life and undertakes

agents are of a Constant Relative Risk Aversion (CRRA) structure. The utility for agents who adopt *Technology A* are described by:

$$U(c^A_{it+1}, b^A_{it+1}) = \left[\frac{(C^A_{it+1})^{1-y} - 1}{1-y} + \frac{\theta(b^A_{it+1})^{1-y} - 1}{1-y} \right] \tag{1}$$

The utility for agents, in the event he/she adopts *Technology B* are described by:

$$U(c^{B,1}_{it+1}, c^{B,h}_{it+1}, b^{B,1}_{it+1}, b^{B,h}_{it+1}) = p \left[\frac{(c^{B,h}_{it+1})^{1-y} - 1}{1-y} + \frac{(b^{B,h}_{it+1})^{1-y} - 1}{1-y} \right]$$
$$+(1-p) \left[\frac{(c^{B,1}_{it+1})^{1-y} - 1}{1-y} + \frac{(b^{B,1}_{it+1})^{1-y} - 1}{1-y} \right] \tag{2}$$

In equation (1), $c_{it+1}$and b_{it+1} denote period 2 consumption and bequests for agent i if he invest in the technology directly. Superscripts l and h represent the nature of shock that the economy is subjected to; h denotes a good shock while l represents a bad shock. In both equation (1) and equation (2), the parameter describes θ the extent of imperfect intergenerational altruism in the model, and y is a measure of the degree of relative risk aversion that is implicit in the preferences. Agents face different budget constraints depending on the technology that they adopt. The budget constraint for an agent who adopts *Technology A* is as follows:

$$c^A_{it+1} = \alpha(\bar{w} + w_{it}) - b^A_{it+1} \tag{3}$$

The state-contingent budget constraint for an agent who adopts Technology B directly is given by:

$$c^{B,h}_{it+1} = (\eta + \varepsilon_{i,h})(\bar{w} + w_{it}) - b^{B,h}_{it+1} \tag{4}$$

$$c^{B,h}_{it+1} = (\eta + \varepsilon_{i,l})(\bar{w} + w_{it}) - b^{B,h}_{it+1} \tag{5}$$

Resource endowments for agent i depends on whether his/her parents adopted *Technology A* or *Technology B*. For an agent whose parents adopted *Technology A* $w_{it} = w^A_{it} = b^A_{it}$. For an agent whose parents adopted *Technology B* $w_{it} = w^B_{it} = b^B_{it}$. Agent i's problem is to optimise his utility subject to his/her budget constraint. Agents who adopt *Technology A* maximise equation (1) subject to constraint (3). This yields the following consumption and bequest plans:

$$c^A_{it+1} = \frac{\alpha}{1+\beta} [\bar{w} + w_{it}] \tag{6}$$

$$b^A_{it+1} = \frac{\alpha\beta}{1+\beta} [\bar{w} + w_{it}] \tag{7}$$

the consumption decision in the second period with his offspring in mind.

Alternatively, the optimal state-contingent plans for agents who adopt *Technology B* directly depend on the shock that the technology faces. These are as follow:

$$c_{it+1}^{B,h} = \frac{(\eta + \varepsilon_{i,h})}{1+\beta}\left[\bar{w} + w_{it}\right] \tag{8}$$

$$b_{it+1}^{B,h} = \frac{\beta(\eta + \varepsilon_{i,h})}{1+\beta}\left[\bar{w} + w_{it}\right] \tag{9}$$

$$c_{it+1}^{B,h} = \frac{(\eta + \varepsilon_{i,i})}{1+\beta}\left[\bar{w} + w_{it}\right] \tag{10}$$

$$b_{it+1}^{B,h} = \frac{\beta(\eta + \varepsilon_{i,i})}{1+\beta}\left[\bar{w} + w_{it}\right] \tag{11}$$

where $\beta = \theta^{1/y}$. It is possible to characterize the agent's decisions to switch to *Technology B* by comparing indirect utility functions for two technologies. Specifically, the i^{th} agent will switch from *Technology A* to *Technology B iff.*

$$U^B(c_{it+1}^*, b_{it+1}^*) \geq U^A(c_{it+1}^*, b_{it+1}^*) \tag{12}$$

Where U^A and U^B denote the indirect utility functions for the agents adopting *Technology A* and *Technology B*. The subscript * denotes the optimal choice of the variables in question. It can then possible to derive the following (See Proof in Appendix 1).

$$\varepsilon_{i,h} < \frac{\eta(\varphi_1 + \varphi_2) + \varphi_1 \varepsilon_{i,h} - \alpha}{\varphi_1}, \tag{13}$$

where $\varphi_1 = p^{\frac{1}{1-y}}$ and $\varphi_2 = (1-p)^{\frac{1}{1-y}}$

2.0.1 Financial Intermediation

To introduce financial intermediation in the model, we assume that agents have an option to adopt *Technology B* through the financial system. In each period t, agents face a decision on whether they adopt *Technology B* directly or through the financial system. For simplicity, we assume that agents who use the financial system achieve full risk diversification. This is because financial intermediaries are able to pool the idiosyncratic risks of individual agents. The return from using financial intermediaries is therefore η. However, each agent faces a fixed cost $c$if he/she decides to use the financial system.[4] We assume that, the c is

[4] This cost often reflects the financial frictions resulting from asymmetric information, adverse selection, moral hazards, etc (see Saint Paul, 1992;Stiglitz and Weiss, 1983; Gale and Hellwig, 1985).

endogenous and depends on the total wealth W_t^F invested through the financial system, which we formally define as follows:

$$W_t^F \quad = \sum_{i=i_{\min}^F}^{i_{\max}^F} (\overline{w} \ + \ w_{it}) = \quad N_t^F (\overline{w} + \overline{\overline{w}}_t^F) \tag{14}$$

where the superscript Fsimply denote the financial system,$i_{\min}^F$ and i_{mac}^F denote the agent with the minimum and maximum wealth who manage to use the financial intermediary, N^Fdenote the total number of agents who use financial intermediaries and $\overline{\overline{w}}_t^F$ is the average wealth of all agents who use the financial system. We consider the following properties for the functional forms of endogenous cost $c(W_t^F)$:

(i) $c'(W_t^F) < 0; c''(W_t^F) \geq 0$.

(ii) $c\frac{(W_t^F)}{K_T^F \to \infty} = 0$

More specifically, we specify the endogenous fixed cost as follows:

$c(K_t^F) \ = \ \left(\frac{N_t^F \ \overline{c}}{N_t^F (\ \overline{w} + \overline{\overline{w}}_t^F \ )} \right) \ = \ \left(\frac{\overline{c}}{(\ \overline{w} + \overline{\overline{w}}_t^F \ )} \right)$, where $\overline{c} \ = \ c(0)$.

The preferences for agents who adopt *Technology B* through the financial system are described by:

$$U(c_{it+1}^{B,F}, \ \ b_{it+1}^{B,F}) = p \left[\frac{(c_{it+1}^{B,F})^{1-\gamma} - 1}{1-\gamma} + \frac{\theta \, (b_{it+1}^{B,F})^{1-\gamma} - 1}{1-\gamma} \right] \tag{15}$$

where all the variables are as defined earlier. The budget constraint for an agent who uses the financial system is described by:

$$c_{it+1}^{B,F} = \eta(\overline{w} \ + \ w_{it} \ ) \ - b_{it+1}^{B,F} \ - \ c(W_T^F) \tag{16}$$

The resource endowment of agents whose parents adopted *Technology B* through the financial system is defined by $w_{it} = w_{it}^{B,F} = b_{it}^{B,F}$. Agents who use the financial system maximise (15) subject to (16). This gives the following consumption and bequest plans.

$$c_{it+1}^F = \frac{1}{1+\beta} \left[\eta(\overline{w} + \ \ w_{it}) - c(W_t^F) \right] \tag{17}$$

$$b_{it+1}^F = \frac{\beta}{1+\beta} \left[\eta(\overline{w} + \ \ w_{it}) - c(W_t^F) \right] \tag{18}$$

Following the same process as above, we can characterise the decision to switch from *Technology A* to *Technology B* through the financial system by comparing the respective indirect utility functions. More specifically the i^{th}agent will switch from *Technology A* to *Technology B* through the financial system *iff.*

$$U^{B,F}(c_{it+1}^*, \ b_{it+1}^*) \quad \geq \quad U^A(c_{it+1}^*, b_{it+1}^*) \tag{19}$$

Combining equation (13) and (19), it is possible to make the following proposition (See Proof in Appendix 1):

Proposition 1*: Let* $w^* = \frac{(\varphi_1+\varphi_2)\,\overline{c}}{\{\alpha[1-(\varphi_1+\varphi_2)]-\varphi_1\varepsilon_{ih}-\varphi_2\varepsilon_{il}\}\left(\overline{w}+\overline{\overline{w}}_t^F\right)} - \overline{w}$ *.An agent will switch from Technology A to Technology B through the financial system iff.* $w_{it} \geq w^*$.

To gain more intuition about w^*, we carry out some comparative static analysis to examine how w^* changes with the parameters of the model and they are reported in Appendix 1.Our results are intuitively plausible; we find that w^* is decreasing in parameters $\overline{w}$, $\overline{\overline{w_t^F}}$, γ, α, ε_{il} and increasing in parameters ε_{ih}, $\overline{c}$, p. This implies that an agent is more likely to adopt *Technology B* through the financial system if the subsistence wage is high, the total wealth invested through the financial system increases, i.e. the financial system becomes deeper, their risk averseness increases, the size of loss from a bad shock increases, and the return on *Technology A* increases. On the other hand agents are less likely to adopt *Technology B* through the financial system if the size of the gain from a good shock and the probability of this shock are large, the initial costs of financial intermediation are high.

The dynamics of the model are described by the evolution of bequests overtime. This is given by the following truncated system of first order difference equations:

$$w_{it+1}^A = \lambda^A \; [\overline{w} + \; w_{it}] \tag{20}$$

$$\left.\begin{array}{ll} w_{it+1}^{B,h} = \lambda^{B,h}\,[\overline{w} + \; w_{it}] \;\; , & with\,probability\,p \\ w_{it+1}^{B,l} = \lambda^{B,l}\,[\overline{w} + \; w_{it}] \;\; , & with\,probability\,(1-p) \end{array}\right\}\} \quad for\ \varepsilon_{i,h} \leq \varepsilon_{i.,h}^* < w^* \tag{21}$$

and

$$w_{it+1}^F = \lambda^{B,F}\,[\,\overline{w} + \; w_{it}] - \beta\overline{c})\,/(1+\beta)(\overline{w} + \overline{\overline{w}}_t^F), \qquad for\;\; w_{it} > \;\; w^* \tag{22}$$

where $w_{it+1} = b_{it+1}$ in equilibrium, $\lambda^A = \frac{\alpha\beta}{1+\beta}$,$\lambda^{B,h} = \frac{\beta(\eta+\varepsilon_{ih})}{1+\beta}$, $\lambda^{B,l} = \frac{\beta(\eta+\varepsilon_{il})}{1+\beta}\lambda^{B,F} = \frac{\alpha\beta}{1+\beta}$, and $w^*$is defined in Proposition 1. The slopesλ^A,$\lambda^{B,l}$, $\lambda^{B,h}$, $\lambda^{B,F}$of the bequests functions represent the productivities of the respective technologies. The dynamics of the model depend on these productivities as well as the endogenous costs $c(W_t^F)$ associated with financial intermediation. Since the focus of this paper is empirical, analyses of the dynamics and the long run outcomes of the model are beyond the scope of the paper. The empirically testable predictions of the model are informed by the comparative statics performed above.

Two empirically testable predictions can be drawn from this simple theoretical model: (i) financial development/deepening has a positive effect on the adoption and diffusion of productive yet risky technologies, (ii) differences in financial development across countries can account for differences in the timing of technology adoption. According to the model, there are two channels through which financial deepening enhance the adoption of technologies. Firstly, it reduces the risk associated with new technologies and thereby helping risk-averse agents to adopt new risky technologies. Secondly, financial deepening reduces the costs of diversifying the risk. In what follows we now empirically analyse these predictions.

3 Empirical Methodology and Data

3.1 Empirical Measures of Technology Diffusion and Timing of Adoption

To address prediction (i), we examine whether financial development has a positive impact on the *intensity* of technology use. In line with Comin and Mestieri (2013), we measure the *intensity* of technology adoption as the units of a technology in use *per* capita or *per* unit of real GDP. The *per* capita *intensive margin* is more appropriate for technologies which are measured in the form of the number of adopters, for example cell phones, computers, internet use, televisions, etc. The *per* unit of real GDP *intensive margin* is more appropriate for technologies that are expressed in the form of new production techniques for example, the number of tractors or harvester machines used in agriculture, the total fertilizer used per hectare, the area equipped with irrigation equipment to total agricultural land, share of cropland cultivated with modern varieties, etc.[5]

To address prediction (ii), we examine whether risk and adoption costs have a negative impact on the timing of technology adoption. The timing of technology adoption is proxied by the technology usage lag. The usage lag of technology $x$in country $c$is at year $t$is simply defined as the number of years before year $t$that a technology leader last had a usage intensity of technology y that country c has in year t. As the standard in the literature, we assume that the technology leader is the US. More formally, let k_{it*}be the intensity of usage of technology$y$ in country $c$at some benchmark year t^*. Let the same level of intensity usage for the U.S. be denoted by $k_{US,\, s}$, where s indexes the observations over time. Let S denote the set of observations available in the historical time series of the U.S. Then two observations $\overline{s}$ and $\underline{s}$ can be defined in the US time series, where $\overline{s}$ denotes the last time when the U.S. passed intensity of usage k_{it*} and $\underline{s}$ denotes the last time the U.S. recorded a usage intensity level lower than or equal to k_{it*}. More formally,

$$\overline{s} \;=\; \arg\min_{s\,\in\, S} \{s : k_{it} \;\geq k_{it*} \; for\; all\; s' \in S \; and\; s' \in s\} \tag{23}$$

and

$$\overline{s} \;=\; \arg\min_{s\,\in\, S} \{s : k_{it} \;\leq k_{it*}\} \tag{24}$$

We then impute the time that the U.S. last had the technology usage intensity k_{it*}, say τ, by linear interpolation, as follows:

$$\tau \;=\; \left(\frac{k_{ct*} - k_{US,\underline{s}}}{k_{US,\overline{s}} - k_{US,\underline{s}}}\right)\overline{s} \;+ \left(\frac{k_{US,\overline{s}} \;-\; k_{ct*}}{k_{US,\overline{s}} - k_{US,\underline{s}}}\right)\underline{s} \tag{25}$$

The technology usage lag between the U.S. and country $c$is then computed as $Lag_c \;= \tau - t$.

[5]It would have been more appropriate scale these technologies by the output they produce, but such data is unavailable.

3.2 *Econometric Approach*

We begin by estimating the *static* fixed-effect panel regressions (18) and (19) to address predictions (i) and (ii).[6] The fixed effects panel regression model controls for possible unobserved cross-country heterogeneities and other omitted variable biases.

$$y^i_{c,t} \;=\; \vartheta_1 + \beta_1 FD^i_{c,t} + \phi_1 X_{c,t} + u_{1i,t} \tag{26}$$

$$Lag^i_{c,t} \;=\; \vartheta_2 + \beta_2 FD^i_{c,t} + \phi_2 X_{c,t} + u_{2i,t} \tag{27}$$

where the subscripts i, c, t respectively denote the technology i, country $c$and year t. *FD* is a measure of financial deepening. We use Bank Credit to the Private Sector as a percentage of real GDP, and the spread between lending and deposit rates of measures of financial development.[7] In line with the predictions above, we expect that a deeper financial system improves technology diffusion. Thus for the measure based on bank credit to private sector, we expect that $\beta_1 > 0$ and $\beta_2 < 0$. For the measure based on interest rate spread, we expect that $\beta_1 < 0$ and $\beta_2 > 0$ since high interest rate spread indicate higher costs of financial intermediation. $\vartheta_1$and $\vartheta_2$are country-specific intercepts, and $u_{1i,t}$ and $u_{2i,t}$ are error terms.

$X_{c,t}$ denotes other determinants of technology diffusion controlled for in the regressions. These include the level of development which is proxied by the log of real GDP, costs of technologies adoption, which are proxied by the inverses life expectancy and the percentage literacy of those above 15 years of age, risk of technologies, which is proxied by the standard errors of the growth in real GDP. For IT and communication technologies, we use standard errors of growth in electricity production and real GDP. For industrial/infrastructural technologies, we use standard errors of real GDP growth. We expect that level of development has a positive effect, while risk and costs has a negative effect on technology diffusion. Finally, we control for the number of years since initial adoption. This is because usage *intensity* is likely to improve as producers and consumers take more time to learn about the technology.

The assumption upon which the *static* panel regressions (18) and (19) are used is that adjustment of the measures of *intensive margin* to their steady state values is quick and happens within the estimation period being used (one year or four year). However, adjustment could be slower resulting in past lags of *intensive margin* explaining the current *intensive margin.* To accommodate for this possibility, we also estimate the following *dynamic* fixed panel regressions.

$$y^i_{c,t} \;=\; \vartheta_3 + \psi_1 y^i_{c,t-1} + \beta_3 FD^i_{c,t} + \phi_3 X_{c,t} + u_{3i,t} \tag{28}$$

$$Lag^i_{c,t} \;=\; \vartheta_4 + \psi_2 Lag^i_{c,t-1} + \beta_4 FD^i_{c,t} + \phi_4 X_{c,t} + u_{4i,t} \tag{29}$$

[6] The Hausmann test statistic was statistically significant at 5 % or less for all the technologies considered. This suggests that the random effect model is not appropriate.

[7] Bank deposit as a percentage of GDP could have reflected the idea of endogenous financial intermediation in our model better. Unfortunately data on bank deposits is not available for many countries.

where $y^i_{c,t-1}$ and $Lag^i_{c,t-1}$denote the values of the dependent variables in period 1.

Estimating regressions (20) and (21) using fixed effects estimators will produce inconsistent results. This inconsistency results from the correlation between the lagged dependent variables ($y^i_{c,t-1}$and $Lag^i_{c,t-1}$) and the respective error terms ($u_{3i,t}$ and $u_{4i,t}$). There is also a possibility that the other explanatory variables (i.e. $FD^i_{c,t}$ and $X_{c,t}$) are correlated to the error terms. To address these issues, we use the dynamic-GMM estimators of Arellano and Bond (1991). These GMM estimators take into account the dynamic nature of the model and the autocorrelation induced by $y^i_{c,t-1}$ and $Lag^i_{c,t-1}$ among the covariates.

In the dynamic-GMM estimation of Arellano and Bond (1991), the current variables are instrumented for using their past lags thereby eliminating potential correlation between the explanatory variables and the error term. Secondly, regression (29) and (30) are derived from their first differenced counterparts. This eliminates unobserved country-specific fixed effects that might explain the cross-country differences in *intensive margins* and timing of adoption across countries.

We test the validity of our estimates using the Sargan test of over-identifying restrictions under the null hypothesis of instrument exogeneity. We also test for autocorrelation in the differenced residuals using the Arellano test for autocorrelation under the null hypothesis of no serial correlation in the error term.

3.3 *Data*

The technology adoption data comprise of 13 technologies from 5 sectors of the economy. These sectors include the agricultural sector, energy sector, information and technology sector, communication sector, and the transport sector. All the 13 technologies are very important to growth and development in Africa. The sample comprises of between $17-44$ SSA countries, depending on the technology in question. The data are sourced from different sources, including the Historical Cross Country Technology Adoption (HCCTA) of Comin and Hobijn (2009), the World Development Indicators (WDI) of the World Bank (2014), and the Food and Agricultural Organisation (2014) database. Data availability varies across the technologies and this influences our choice sample of analysis. Details relating to the technologies explored, the sample period analysed, number of countries covered, other explanatory variables used and data sources are presented in Table 1.

4 Empirical Results

4.1 *Financial Development, Diffusion and Timing of Adoption*

We begin by estimating static panel regression (28) and its dynamic counterpart (30) to examine the role of financial deepening on technology diffusion. The results are reported in Tables 2 and 3. Generally the results from both the static and dynamic panel models support the idea in the theoretical model developed above, and the literature on growth and finance (see Levine, 2001 for detailed review) that financial deepening has a positive impact on the diffusion of sectoral technologies. However, the economic and statistical significance of coefficients of financial deepening vary across the technologies. In the static panel, the coefficients for financial deepening are much economically strong for the following technologies: mobiles, internet, newspapers, television, computers, and fertilizer. The differences in coefficients may highlight the ease with which these different technologies are financeable through the financial system. For example, technologies with large capital intensity (e.g. commercial vehicles, tractors, electricity, telephone, etc.) tend to require sizeable collateral, and are thus difficult to finance at agent level. This explains why their coefficients on financial deepening are low.

Another interesting result is that the coefficient of financial deepening for tractors is negative in the static model, but positive in the dynamic panel model. This might be an indication of misspecification issues with the static model. Indeed the results from the dynamic panel model suggest that lagged values have a positive and significant influence on their current values for all the technologies questioning the appropriateness of the static model. This result also supports two ideas in our models. Firstly it supports the idea that the technology adopted by an agent depends on the wealth that agents inherit, which in turn depends on the technology that their parents adopted i.e. the higher the number of agents adopting *Technology B* the more will agents adopt *Technology B* in the next period. Secondly, it supports the idea highlighted by endogenous financial deepening in our theoretical model. That is as more agents adopt *Technology B* through the financial system in the current period, the cost of financial intermediation decrease and more agents adopt *Technology B*. From an empirical modelling point of view, this result implies that the dynamic panel model is more appropriate as it captures these lagged effects.

The coefficients of other control variables (such as GDP, primary school enrolment), etc. are as expected in most of the specifications. In most of the cases where coefficients are incorrectly signed, they are statistically insignificant. For technologies whose sample begins after 1996 (computers, mobile phones, and internet), we control for institutional quality as proxied by control of corruption.[8] Generally, the results show that high institutional quality in the form of the ability to control corruption positively enhances technology diffusion. This result underscores the role of high quality institutions in economic development as emphasized in studies such as Acemoglu (1999) and La Porta (1997, 1999, 2000).

Next we estimate regressions (29) and (31) to examine the impact of financial development on the lag of adoption. The results are reported in Tables 4 and 5.

[8] The data on institutional quality is based on World Governance Indicators (WGI) and only available from 1996 to 2012. There are five WGI. We experimented with all the indicators and results are qualitatively similar. For brevity, we only report the results based on control of corruption.

Qualitatively, the results have very few distinctions from those on diffusion of technologies. Financial deepening reduces the lag adoption i.e. it quickens the timing of technology adoption. Our explanation is in line with that provided above that, a deeper financial system promotes efficient lending and borrowing and thus the easy adoption of new technologies. As is the case with diffusion of technology, the impact of financial depth on the lag of adoption varies depending on the capital intensity of the technologies. The coefficients of the other determinants of lag technology adoption are mostly correctly signed and significant. The importance of high quality institutions in timing of technology adoption is also evident. The results from dynamic panel model suggest the presence of significant lagged effects in all the technologies.

4.2 *Robustness Checks*

In this section we examine whether the impact of financial deepening on the timing of adoption and the diffusion of technology is robust to different sensitivity tests. Four sensitivity tests are carried out. First, we explore the idea in our theoretical model and other models that financial deepening encourages technology adoption and diffusion by reducing the risk/uncertainty associated with productive technologies. Second, we use an alternative measure of financial deepening, the spread between the lending and deposit rate. This measure captures the efficiency of financial intermediation. A deeper financial system is likely to be more efficient and thus have a low interest rate spread. Third, we examine whether the level of development has an impact on technology diffusion and timing of adoption. This empirical examination derives from our *Proposition* 1, i.e. that there is the threshold level of wealth that is required to adopt a more productive technology. Fourth, we construct weighted aggregate measures of sectoral technology from the individual technologies and then examining whether financial deepening still influences these aggregate measures. Fifth, we use alternative measures of risk. In light of the presence of lagged effects in all the technologies, all our sensitivity tests are carried out using the dynamic panel GMM. Fourth, we drop the two biggest economies in SSA, Nigeria and South Africa and re-estimate the models based on the remaining countries. In what follows, we now explore each of these sensitivity tests in detail.

Is the Effect of Financial Depth on Technology Adoption Direct or Indirect?

According to our model, financial depth can influence technology adoption by reducing the level either directly by reducing the threshold wealth required to access the more productive technology, or indirectly by reducing risk. To examine these issues, we create a variable based on interacting the measures risk (volatility of GDP) and financial deepening. We then re-estimate the above regressions by controlling for this new variable, financial depth, risk, along with other explanatory variables. The results for technology diffusion are reported in Table 6 while those for timing of technology adoption are reported in Table 7. From Table 6, it is evident that the coefficients of financial deepening are still positive and significant confirming the role of finance in enhancing technology diffusion. Most of the coefficients of GDP volatility are negative and significant. This implies that risk delays the diffusion of technologies. The coefficient of the term of interaction between financial deepening and risk is positive. This is consistent to the intuition in our theoretical model that financial deepening enhances technology diffusion through helping agents to diversify risk. As before, most of the coefficients of the log of GDP are positive and significant. Most of the coefficients educations (i.e. primary school completion) are positive, but few are significant. The coefficients of regulatory are also mostly positive, but not always significant.

As for Table 7, it is evident that the coefficients of financial deepening are still negative and significant confirming the importance of the financial system in enhancing early timing of technology adoption. Most of the coefficients of GDP volatility are positive and some are significant. This implies that risk delays the timing of technology adoption. Nine out ten of the coefficients of the interaction term between volatility/risk and financial development are negative, and half of them significant. This suggests that financial deepening enhances early adoption of technology by diversifying away the risk associated with these technologies. Most coefficients of GDP are positive suggesting that the level of wealth is associated with a delay in technology adoption. This is surprising as one would expect that an increase in wealth will result in quicker adoption of technologies. This implies, then, that there might a factor(s) that this result. We therefore explore this result further below.

Are the Results Biased to the Measure of Financial Deepening?

It is possible that as a country becomes technologically advanced, bank lending increases, resulting in the possibility that causality runs from technology diffusion/adoption to financial adoption. Although this issue has been addressed by instrumenting bank credit with its past lags in our dynamic GMM panel estimation, it is possible that this endogeneity is not fully addressed, and thus our finding may be picking from the measure of financial depth. To address this issue, we use an alternative measure of financial deepening, the spread between the lending rate and the deposit rate. Unlike bank lending, the interest rate spread is less likely to be influenced by technology adoption. This is because, although technology adoption may affect interest rate, it can affect both the deposit rate and lending rate in the same fashion. Thus it is less likely to influence the spread between the two rates. Furthermore, in our GMM estimation, we use past lags of interest rate spread as instruments, making the potential endogeneity even less probable. The results for technology diffusion are reported in Table 8, while the results for timing of technology adoption are reported in Table 9.

In Table 8, it is evident that the coefficients of the interest rate spread are negative and significant. This implies that an increase in financial sector inefficiency, as shown by the widening spread between lending rate and the deposit rate is associated with a slower diffusion of technologies. The results in Table 9 show that most of the coefficients of interest rate spread are positive and significant. This implies that an increase in financial market inefficiencies is associated with delays in the timing of technology adoption. These results are intuitively appealing given that financial sector inefficiencies increase the cost of borrowing and diversifying risk. The coefficients of the other explanatory variables of interest are quite consistent with those from previous results.

Level of Development, Technology Diffusion and Timing of Adoption

A surprising result emerging from above is that an improvement in the level of development as proxied by GDP does not seem to consistently enhance early adoption and quicker diffusion of technologies. A possible explanation for this result could be based on the existence of a threshold in level of development as in *Proposition* 1 of our model. More specifically, the level of wealth (GDP) relative to the threshold level, $w*$might be what matter for technology adoption and not the changes in wealth. In that case the wealth may increase, but as long as it remains below the threshold, it has little or no consequence for adoption and diffusion.

To address, we control for the level of development. This is done by first computing the average level of GDPPK for the SSA counties. We then use a dummy variable, which takes the value 1 if a country whose GDPPK is above computed average GDPPK, and 0 if otherwise. The dummy variable is then included as an explanatory variable, along with other explanatory variables.

The results are on technology diffusion are reported in Table 10 and those for timing of adoption are reported in Table 11. The signs coefficients of the log of GDP remain mixed in both timing and diffusion equations. The coefficients of the dummy are all negative and mostly significant in the regressions for timing of adoption suggesting that countries above a certain threshold level of development adopt technologies earlier than those below. However, in the regressions for diffusion of technologies, the coefficients have mixed signs. More specifically, the dummy variable has negative signs for technologies such as internet, electricity, computers, and a positive sign for technologies such as irrigation, combine harvesters, fertilizer application, etc. This result seems to suggest that the rate of diffusion of some technologies slows down once countries have surpassed a certain threshold level of development. This might, in part, explain why the rate of diffusion of mobile phones (and other inventions associated with mobiles, e.g. mobile money transfers) in SSA has outpaced the diffusion for many high income countries over the past few years (ECA, 2013 and 2014).

Using Aggregate Measures of Technology Adoption

Next we construct three aggregate technology adoption indices for the agricultural, communication, and the information sectors.[9] This exercise is only applicable for diffusion of technologies and not timing of technology adoption. In constructing the technology adoption indices, we follow an approach in Jain *et al.* (2009), which is also related to the approach used by the United Nation Development Program (2006) to compute the Human Development Index. We begin with standardising each of the indicators of technology adoption as

[9] The indexes are composed as follows: information sector includes internet and mobiles while the communication sector includes newspapers, radio, and television and the agricultural sector includes tractors, fertilizer, and two proxies of irrigation. The sample period influenced the choice of variables for the aggregate index. See Table 1 for the sample.

follows:

$$X_i = \frac{X_i - X_{\min}}{X_{\max} - X\min} \tag{30}$$

Where $X_i$is the i^{th}value of the technology adoption indicator in question, X_{min}, X_{max} denotes the minimum value and the maximum value of this indicator, respectively. Once all the indicators are standardised, we now use normalised weights (denoted by α_i for technological indicator i) obtained from a Principal Component Analysis (PCA) to compute the aggregate technology adoption indexes which is given by:

$$TAI = \sum_{i=1}^{6} \alpha_i X_i \tag{31}$$

These indices take values strictly between 0 and 1, with a higher value indicating a larger extent of technology adoption. Using these aggregate measures, we then re-estimated the heteroscedastic-robust fixed effect models. The results are presented in Table 12.

In Table 12, regression (1) to (5) presents the results based on the on the information aggregate technology index, regressions (6) and (7) present the results based on agricultural aggregate technology index, and regressions (8) to (10) are for technologies based communication aggregate technology index. As expected, all the coefficients of financial deepening are positive and significant. Most of the coefficients of the proxy of risk are negative and significant confirming the role of risk in slowing diffusion of technologies. The coefficients of the interaction term between risk and financial deepening, and half of them are significant reinforcing the fact that financial deepening affects technology diffusion by reducing risk. Interestingly, all the coefficients of log of real GDP are positive and most are significant. All the coefficients of the dummy variable for level of development are also positive and eight out of ten are statistically significant. The coefficients of education are correctly significant but not significant. The coefficients of regulatory quality are positive and significant underscoring the importance of good quality institutions in technological deepening.

4.3 *Analysis of Results*

Overall the empirical analysis gives indirect support to the main predictions of our model that financial development enhances technology deepening, and they underscore the role played by the financial sector in development as emphasized in authors such as Greenwood and Jovanovic (1990), King and Levine (1993), and Levine (2003), among others. Furthermore, the results are in line with the theoretical intuition in our model, and in models such as Greenwood and Jovanovic (1990), Saint-Paul (1992) and Obstfeld (1994) that the financial system encourages the adoption of high risk, high return technologies/projects by offering means of diversifying the risk. The level of development matters particularly for the timing of technology adoption decision, and this supports the prediction of our model.

5 Concluding Remarks and Policy Implications

The paper examines the role of financial deepening in the timing of technology adoption and the diffusion of productivity-enhancing sectoral technologies in 44 African countries. The underlying motivations for this study stem from two distinct, yet related pieces of literature and empirical observations. The first is the evidence suggesting the divergences in the pace of technological advancements, and differences in growth experiences across developing countries. The second relates to the role of the financial system in economic development as has been extensively documented in theoretical and empirical literature. The contribution of the current paper is in reconciling these two issues by examining whether differences in financial markets depth can explain the differences in the timing of technology adoption and the rate of technology diffusion.

To that end, we begin by developing a simple endogenous growth model in which growth takes place through physical and human capital deepening, and risk-averse agents are heterogeneous in their initial resource endowments. The agents face the choice of adopting either of the two technologies available in the economy, a safe low return, and risky, but high return technology. The risk associated with the high return technology can be diversified away by sing the financial system. Entry in the financial system is subject to a fixed cost that is endogenous in the total wealth invested through the financial system.[10] The results from the model show that there is a threshold level of wealth that is required for an agent to use the financial system and this threshold is decreasing the level of financial deepening. This implies that financial deepening is likely to enhance early adoption of technologies and improve the pace of technology diffusion by reducing risk.

We then empirically test this theoretical prediction using a panel consisting of 44 SSA countries and thirteen sectoral technologies. The results are indeed consistent with our theoretical prediction, although the economic significance of coefficients varies across technologies. The results also show the effects of financial depth on the timing of technology adoption and the speed of technology diffusion manifest both directly, and indirectly through reducing the risk associated with the productive technologies. The results are robust to a number of stringent tests, including more robust estimation approaches, different proxies of financial depth, controlling for different factors that influence technology adoption and using aggregate measures of technology diffusion.

There is also evidence to suggest that the impact on financial depth on the timing of technology adoption is stronger for counties that have reached a certain threshold level of development. However, when it comes to diffusion of technologies, the impact of the level of development varies across individual technologies, with some technologies having negative and significant coefficients for the proxy level of development. This latter result underscores the idea that some technologies may actually diffuse faster in low income countries. The faster penetration of mobile phones and their accompanying innovations in Africa than

[10] The total wealth invested through the financial system can be interpreted as an indicator of the level of financial depth.

in more developed regions of the world is one of such an example. However, when we use aggregate measures of technology diffusion, all coefficients of the proxy for level of development are positive and significant. Finally there is evidence suggesting that the structural elements of the economy, as shown by a proxy of education, and institutional elements of the economy, as proxied by regulatory quality enhance the timing and the diffusion of technologies.

The findings of the study have a number of policy implications, especially in relation to mobilizing sectoral technologies for the industrialization and structural transformation of Africa. The first policy implication relates to the role of financial deepening in facilitating the mobilization of domestic financial resources to finance development. African countries indeed recognise the role of deepening the domestic financial system in improving domestic resource mobilization. They have highlighted this within Pillar 6 of the CAP on the post-2015 development agenda. A deep financial system will ensure effective diversification of risk and efficient channelling of financial resources towards priority sectors. It will therefore ensure sooner adoption and quicker diffusion of technologies within these sectors. Consequently the pace of industrialization, structural transformation, and economic diversification will be improved.

However, it is important to emphasize that financial depth alone is not sufficient to achieve a more inclusive industrialization and structural transformation. As emphasized in many studies (see Rosenzweig and Stark, 1989; Townsend, 1995; Udry, 1994; Dercon, S. and Christiaensen, 2011)and also evident in our theoretical model, risk is mostly binding to technology adoption decisions of poor households whose initial resource endowment is too far below the threshold required to access risk-diversifying institutions. More specifically, financial access is more important than financial deepening for the poor agents. Unfortunately, due to unavailability of financial access data, we only focussed on the role of financial depth. Given the recent developments in innovative banking solutions, for example mobile and internet banking, it is expected that financial inclusion will improve in Africa and richer data on financial access will become available. We therefore leave the role of financial access on technology adoption and diffusion for future research.

The findings of this paper also highlight that strengthening the human capital is important if African countries are to successfully adopt and diffuse productive technologies in order to industrialize and structurally transform their economies. Poor human capital does not only impose a cost on technology adoption, but also on other aspects of development. Given that Africa's population is expected to double to approximately 2.4 billion by 2050 (Ken and Haub, 2005), making Africa the world's source of workforce, investing in human capital development will enable the continent to take advantage of this opportunity. To date, Africa has made progress in human development. For example, gross secondary school enrolment has almost doubled since 1990, enrolment in tertiary sector has more than doubled for men and tripled for women, access to health has improved resulting in approximately 50 per cent reductions in child, infant and maternal mortalities, and urbanization has significantly improved (AfDB, 2014). Despite these improvements, Africa still lags behind other regions in a number of human capital development indicators. Consequently, more investment in health and education is necessary to turn Africa's population growth into an opportunity for enhancing an inclusive industrialization and structural transformation.

Finally, in light of the finding that institutional quality is important for technological advancement and development, a policy implication of this is that Africa needs to keep on strengthening its efforts to improve governance and institutional quality. Good public and corporate governance are also key to efficient mobilization and allocation of financial resources. Many African governments, regional and continental institutions are increasingly appreciating that poor governance is inextricably linked to poor economic performance, fragility, and social unrest (AfDB, 2014). To that end, they are making efforts to strengthen institutions of accountability and the rule of law. These efforts have already started yielding dividend in some African nations. For example, a quarter of the 50 world economies whose regulatory environment for business improved between 2007 and 2013 are from sub-Saharan Africa (World Bank and International Finance Corporation, 2013). Eight of these sub-Saharan countries were ranked ahead of China – which was the best ranked in the BRIC, 11 were ranked ahead of Russia, 16 were ranked ahead of Brazil and 17 were ranked ahead of India (World Bank and International Finance Corporation, 2013).

Therefore Africa is on the right track and is increasingly taking responsibility for its developmental policies. In fact its proposed post-2015 agenda lays out a comprehensive plan on how the continent intends to collectively move forward in ensuring industrialization, structural transformation, and inclusive growth by addressing issues such as technological and infrastructural backlogs, human capital development, environmental sustainability, governance, peace and security, financing, among others. It is yet to be seen whether this plan will be appropriately implemented to achieve its intended objectives.

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Table 1: List of Technologies and other Variables

No	Description and (Number of countries)	Name (Period)	Source
1	No. of self-propelled machines that reap and thresh in one operation (**17**)	harvester (1980-2001)	Comin and Hobijn (2009).
2	No. of wheel and crawler tractors (excluding garden tractors) used in agriculture (**28**)	tractor (1980-2001)	Comin and Hobijn (2009).
3	No. of users of portable cell phones (**44**)	Mobile (1996-2012)	Comin and Hobijn (2009).
4	No. of self-contained computers designed for use by one person (**37**)	Computer (1996-2012)	Comin and Hobijn (2009).
5	Gross Electricity Production in KwHr (**20**)	Elecprod (1980-2001)	(WDI), World Bank (2014).
6	Financial Development = Bank Credit to the Private Sector as a % of GDP	FD (1980-2012)	(WDI), World Bank (2014)
7	Financial Depth = Lending rate minus deposit rate	Ir_spread (1980-2012)	WDI, World Bank (2014)
8	Metric tons of fertilizer consumed. (**31**)	Fertlizer (1980-2001)	Comin and Hobijn (2009).
9	No. of people with access to the worldwide network (**42**)	Internet (1996-2012)	(WDI), World Bank (2014).
10	Area equipped to provide water to crops, including those with full and partial control irrigation or spate irrigation and equipped wetland or inland valley bottoms (**32**)	irrigated (1980-2001)	Comin and Hobijn (2009).
11	No. of newspaper copies circulated daily. (**31**)	newspaper (1980-2001)	Comin and Hobijn (2009).
12	Irrigated area (as defined above) as a share of cultivated land, which includes land used for permanent and temporary crops, pasture, land used for temporary crops. (**32**)	pctirrigated (1980-2001)	Comin and Hobijn (2009).
13	No. of mainline telephone lines connecting a customer's equipment to the public switched telephone network as of year end. (**21**)	Telephone (1980-2001)	Comin and Hobijn (2009).
14	No. of television sets in use. (**29**)	TV (1980-2001)	Comin and Hobijn (2009).
15	No. of commercial vehicles (e.g. buses and taxis, excluding tractors and similar vehicles), in use. (**17**)	Vehicle (1980-2001)	Comin and Hobijn (2009).
16	Population	Population (1980-2012)	Maddison (2007),
17	Log of Real GDP (GDP measured in US$)	LGDP (1980-2012)	WDI, World Bank (2014)
18	Growth in Real GDP	Growth (1980-2012)	WDI, World Bank (2014)
19	Volatility in National Rain Index	VolNRI (1960-2001)	FAO AQUASTAT, 2013
20	Volatility in Gross Production Value	VolGPV (1960-2001)	FAOSTAT (2013)
21	Volatility in Real GDP	VolGDP (1980-2001)	WDI, World Bank (2014)
22	Log of Real GDP per Capita	LGDPPK	WDI, World Bank (2014)

Appendix 1

Proof of Equation (17)

Agent will switch from *Technology A* to *Technology B* directly *iff*.

$$U^B(c^*_{it+1}, b^*_{it+1}) \quad \geq \quad U^A(c^*_{it+1}, b^*_{it+1})$$

Substituting for the functional forms of the utility function and recognising that $b_{it+1} = \beta c_{it+1}$ we get,

$$p\left[\frac{(c^{B,h}_{it+1})^{1-\gamma}-1}{1-\gamma}+\frac{\theta(\beta c^{B,h}_{it+1})^{1-\gamma}-1}{1-\gamma}\right]+(1-p)\left[\frac{(c^{B,l}_{it+1})^{1-\gamma}-1}{1-\gamma}+\frac{\theta(\beta c^{B,l}_{it+1})^{1-\gamma}-1}{1-\gamma}\right]\geq\left[\frac{(c^{A}_{it+1})^{1-\gamma}-1}{1-\gamma}+\frac{\theta(\beta c^{B,l}_{it+1})^{1-\gamma}-1}{1-\gamma}\right]$$

Recall that $\beta=\theta^{1/\gamma}\Rightarrow\beta^{1-\gamma}=\theta^{\frac{1-\gamma}{\gamma}}=\theta^{\frac{1}{\gamma}-1}\Rightarrow\theta\beta^{1-\gamma}=\theta^{\frac{1}{\gamma}}$.Using this we write the above inequality as follows:

$$p(1-\beta)\frac{(c^{B,h}_{it+1})^{1-\gamma}}{1-\gamma}+(1-p)(1-\beta)\frac{(c^{B,l}_{it+1})^{1-\gamma}}{1-\gamma}-\frac{1}{1-\gamma}-\frac{\theta}{1-\gamma}\geq(1-\beta)\frac{(c^{A}_{it+1})^{1-\gamma}}{1-\gamma}-\frac{1}{1-\gamma}-\frac{\theta}{1-\gamma}$$

We can then simply the above inequality as follows:

$$p(c^{B,h}_{it+1})^{1-\gamma}+(1-p)(c^{B,l}_{it+1})^{1-\gamma}\geq(c^{A}_{it+1})^{1-\gamma}$$

Rewriting c^{A}_{it+1}, $c^{B,l}_{it+1}$, $c^{B,h}_{it+1}$ in terms of their definitions in steady state equations (7), (8), (10) we obtain the following:

$$c^h_{it+1}=p\left(\frac{(\eta+\varepsilon_{i,h})}{1+\beta}\left[\overline{w}+W_{it}\right]\right)^{1-\gamma}+(1-p)\left(\frac{(\eta+\varepsilon_{i,l})}{1+\beta}\left[\overline{w}+W_{it}\right]\right)^{1-\gamma}\geq\left(\frac{\alpha}{1+\beta}\left[\overline{w}+W_{it}\right]\right)^{1-\gamma}$$

Following exponential laws and further simplifying, the above inequality simplifies to

$$\varepsilon_{i,h}<\frac{\eta(\varphi_1+\varphi_2)+(1-p)^{\frac{1}{1-\gamma}}.\varepsilon_{i,h}-\alpha}{p^{\frac{1}{1-\gamma}}}$$

Proof of Proposition 1

Agent will switch from *Technology A* to *Technology B* directly *iff.*

$U^{F,B}(c^*_{it+1}, b^*_{it+1}) \quad \geq \quad U^{A}(c^*_{it+1}, b^*_{it+1})$

Following the same process as in the previous page, we can get the following inequality:

$$\eta^{B,h} \geq \frac{\bar{c}}{(\bar{w}+\bar{\bar{w}}^F_t)(\bar{w}+w_{it})} + \alpha$$

Now solving inequality (13) for we obtain:

$$\eta^{B} \geq \frac{\alpha - \varphi_1\varepsilon_{i,h} - \varphi_2\varepsilon_{i,l}}{\varphi_1+\varphi_2}$$

In the above, η^B and $\eta^{B,F}$ simply denote some η that would endogenously results in the event that an agents adopt *Technology B* directly and through the financial system, respectively. Agents who adopt *Technology B* would prefer to use the financial system rather the adopting directly *iff.* $\eta^{B,F} > \eta^B$, and writing this in terms of the above condition we obtain:

$$\frac{\bar{c}}{(\bar{w}+\bar{\bar{w}}^F_t)(\bar{w}+w_{it})} \geq \frac{\alpha - \varphi_1\varepsilon_{i,h} - \varphi_2\varepsilon_{i,l}}{\varphi_1+\varphi_2}$$

Now, solving the above inequality for w_{it} we obtain Proposition 1 i.e.:

$$w_{it} \geq \frac{(\varphi_1+\varphi_2)\,\bar{c}}{\left\{\alpha[1-(\varphi_1+\varphi_2)] - \varphi_1\varepsilon_{ih} - \varphi\varepsilon_{il}\right\}\left(\bar{w}+\bar{\bar{w}}^F_t\right)} - \bar{w}$$

Comparative Statics on Proposition 1

$$\frac{\partial w^*}{\partial \bar{c}} = \frac{(\varphi_1+\varphi_2)\,\bar{c}}{\left(\alpha[1-(\varphi_1+\varphi_2)] - \varphi_1\varepsilon_{ih} - \varphi\varepsilon_{il}\right)\left(\bar{w}+\bar{\bar{w}}^F_t\right)} > 0$$

$$\frac{\partial w^*}{\partial \bar{\bar{w}}} = -\frac{(\varphi_1+\varphi_2)\,\bar{c}}{\left(\alpha[1-(\varphi_1+\varphi_2)] - \varphi_1\varepsilon_{ih} - \varphi\varepsilon_{il}\right)\left(\bar{w}+\bar{\bar{w}}^F_t\right)^2} - 1 < 0$$

$$\frac{\partial w^*}{\partial \bar{\bar{w}}^F_t} = -\frac{(\varphi_1+\varphi_2)\,\bar{c}}{\left(\alpha[1-(\varphi_1+\varphi_2)] - \varphi_1\varepsilon_{ih} - \varphi\varepsilon_{il}\right)\left(\bar{w}+\bar{\bar{w}}^F_t\right)^2} < 0$$

$$\frac{\partial w^*}{\partial \bar{\alpha}} = -\frac{(\varphi_1+\varphi_2)\,\bar{c}\,(1-\varphi_1-\varphi_2)}{\left(\alpha[1-(\varphi_1+\varphi_2)] - \varphi_1\varepsilon_{ih} - \varphi\varepsilon_{il}\right)\left(\bar{w}+\bar{\bar{w}}^F_t\right)^2} < 0$$

$$\frac{\partial w^*}{\partial \varepsilon_{i,h}} = \frac{(\varphi_1+\varphi_2)\,\bar{c}\,\varphi_1}{\left(\alpha[1-(\varphi_1+\varphi_2)] - \varphi_1\varepsilon_{ih} - \varphi\varepsilon_{il}\right)^2\left(\bar{w}+\bar{\bar{w}}^F_t\right)} > 0$$

$$\frac{\partial w^*}{\partial \varepsilon_{i,l}} = -\frac{(\varphi_1+\varphi_2)\,\bar{c}\,\varphi_2}{\left(\alpha[1-(\varphi_1+\varphi_2)] - \varphi_1\varepsilon_{ih} - \varphi\varepsilon_{il}\right)^2\left(\bar{w}+\bar{\bar{w}}^F_t\right)^2} < 0$$

$$\frac{\partial w^*}{\partial p} = \frac{\bar{c}\,((\varphi_1^{\gamma} + \varphi_2^{\gamma})\left[(\alpha + \varepsilon_{i,h})\varphi_1^{\gamma} + (\alpha + \varepsilon_{i,l})\varphi_2^{\gamma}\right]}{(1-\gamma)\left(\overline{w} + \overline{\overline{w}}_t^{F}\right)\left(\alpha[1-(\varphi_1+\varphi_2)] - \varphi_1\varepsilon_{ih} - \varphi\varepsilon_{il}\right)^2} > 0$$

$$\frac{\partial w^*}{\partial \gamma} = \frac{1}{(1-\gamma)^2}\left\{\frac{\varphi_1 \ln p + \varphi_2 \ln(1-p)}{(\varphi_1+\varphi_2)} + \frac{\varphi_1(\alpha+\varepsilon_{ih})\ln p + \varphi_2(\alpha+\varepsilon_{il})\ln(1-p)}{\left(\alpha[1-(\varphi_1+\varphi_2)] - \varphi_1\varepsilon_{ih} - \varphi\varepsilon_{il}\right)}\right\} < 0$$

Appendix 2: Tables of Results

Table 2: Technology Diffusion and Financial Development: Static Panel Regression

	(1) Computer	(2) Electricity	(3) Fertilizer	(4) Harvest	(5) Internet	(6) Irrigated	(7) Mobile	(9) Newspaper	(8) pctirrigated	(10) Telephone	(11) TV	(12) Tractor	(13) Vehicle_Com
Bank Credit	0.039**	0.003***	0.079***	0.0002***	0.028**	0.0001***	2.592***	0.538***	0.0001***	0.0887**	0.242**	-0.002***	0.0001***
	(0.017)	(0.001)	(0.024)	(0.0001)	(0.013)	(0.00002)	(0.759)	(0.068)	(0.00002)	(0.0362)	(0.095)	(0.001)	(0.00002)
Log GDP	4.427**	0.302***	0.085***	0.0003*	9.279***	0.00004*	0.032*	31.96***	0.0212***	7.809***	64.72***	0.005***	0.020***
	(1.763)	(0.113)	(0.030)	(0.0002)	(1.524)	(0.00002)	(0.018)	(4.136)	(0.002)	(0.962)	(5.681)	(0.001)	(0.002)
PriCompletion	0.040*	-0.001	-0.002	0.0001	18.36***	0.0001***	1.340	-0.223***	-0.00006	-0.0001	0.012	8.798**	-0.0001***
	(0.021)	(0.002)	(0.02)	(0.0001)	(6.046)	(0.00003)	(0.927)	(0.054)	(0.00005)	(0.0001)	(0.042)	(4.023)	(0.00002)
Reg. Quality	2.461**				2.541***		1.230						
	(0.976)				(0.660)		(16.60)						
Irrigatedarea			-0.016*	-0.477									
			(0.009)	(0.639)									
Fertilizer						0.0007***			6.62e-09			0.009***	
						(0.0002)			(9.01e-09)			(0.003)	
Constant	-1.851**	-2.642**	4.200***	0.025***	-73.50***	0.015***	-68.84***	-287.9***	-0.189***	-167.4***	-599.8***	0.348***	-0.182***
N	204	349	376	144	328	253	212	324	375	156	370	312	164
R-squared	0.320	0.051	0.057	0.198	0.475	0.246	0.407	0.298	0.268	0.397	0.323	0.230	0.547

Robust Standard Errors in parenthesis; *,**,*** imply 10%, 5%, 1% significance levels, respectively.

Table 3: Technology Diffusion and Financial Development: Dynamic Panel Regression

	(1) Computer	(2) Electricity	(3) Fertilizer	(4) Harvest	(5) Internet	(6) Irrigated	(7) Mobile	(8) Newspaper	(9) pctirrigated	(10) Telephone	(11) TV	(12) Tractor	(13) Vehicle_Com
Lag	0.912***	0.890***	0.701***	0.939***	1.047***	0.792***	0.945***	0.934***	0.963***	1.022***	0.893***	0.724***	0.763***
	(0.045)	(0.017)	(0.042)	(0.019)	(0.017)	(0.023)	(0.024)	(0.018)	(0.049)	(0.021)	(0.014)	(0.041)	(0.051)
Bank Credit	0.019***	0.0002	0.043*	0.0001**	0.051***	0.00004**	0.287***	0.118***	0.0001**	-0.001	0.081***	0.0012	0.00002
	(0.006)	(0.0003)	(0.025)	(0.00003)	(0.013)	(0.00002)	(0.081)	(0.036)	(0.00002)	(0.01)	(0.027)	(0.0014)	(0.00003)
Log GDP	1.185	-0.0228	0.0398*	-0.0000196	2.432***	-0.00393***	-0.0193	8.862***	0.00706**	1.067***	5.499**	0.000145	0.009***
	(0.750)	(0.0382)	(0.0214)	(0.0000809)	(0.562)	(0.00129)	(0.0555)	(1.829)	(0.00308)	(0.236)	(2.650)	(0.00100)	(0.003)
Prim Complete	0.034	-0.0002	-0.055***	0.006	0.638	0.032	0.182***	-0.0233	0.000004	1.478	-3.021***	0.0009	0.00005
	(0.032)	(0.0003)	(0.019)	(0.006)	(1.461)	(0.104)	(0.045)	(0.0213)	(0.00002)	(1.068)	(0.882)	(0.001)	(0.0001)
pctirrigated			-0.006	-1.100**									
			(0.008)	(0.459)									
Investment to GFCF		-0.014											
		(0.010)											
Reg. Quality	-0.441				0.161		1.101						
	(0.392)				(0.373)		(1.461)						
Fertilizer									-1.43e-09			0.008***	
									(5.50e-09)			(0.003)	
2^{nd} Order Corr	-0.07(0.94)	1.05(0.29)	1.20(0.23)	0.97(0.34)	-0.09(0.93)	-1.13(0.21)	0.33(0.74)	-0.26(0.80)	-1.23(0.21)	0.74(0.93)	-0.42(0.93)	1.02(0.34)	-1.43(0.14)
Sargan	83.2(0.42)	74.9(0.48)	188.9(0.18)	83.35(0.41)	48.55(0.73)	90.84(0.25)	31.83(0.87)	67.58(0.59)	58.63(0.67)	49.92(0.74)	163.7(0.03)	63.09(0.66)	51.25 (0.71)
N	158	565	282	234	577	392	339	244	292	344	550	233	131

Robust Standard Errors in parenthesis; *,**,*** imply 10%, 5%, 1% significance levels, respectively.

Table 4: Timing of Technology Adoption and Financial Development: Static Panel Regression

	(1) L-Electricity	(2) L-Fertilizer	(3) L-Harvest	(4) L-Irrigated	(5) L-Newspaper	(6) L-pctirrigation	(7) L-Telephone	(8) L-TV	(9) L-Tractor	(10) L-Vehicle
Bank Credit	-0.208***	-0.223***	-0.256***	0.005	-0.141***	-0.100***	-0.356***	-0.065*	-0.064	-0.155***
	(0.061)	(0.031)	(0.055)	(0.006)	(0.032)	(0.024)	(0.076)	(0.034)	(0.041)	(0.027)
Log GDP	-4.417	42.77***	43.85***	-2.739***	45.40***	0.0249	5.033**	25.60***	2.563**	39.72***
	(6.055)	(1.920)	(3.276)	(0.782)	(1.923)	(0.0655)	(2.003)	(2.028)	(1.246)	(1.690)
Primary Complete	0.144**	-0.109***	-0.107*	-0.007	-0.043*	0.061	0.013	-1.713	-0.055	-7.530
	(0.057)	(0.025)	(0.058)	(0.009)	(0.025)	(0.038)	(0.040)	(1.871)	(0.040)	(23.56)
Irrigatedarea		0.0703***	0.0562***							
		(0.0114)	(0.0116)							
Fertilizer				0.0241		0.00004**			-0.414**	
				(0.0402)		(0.00002)			(0.184)	
Constant	182.9***	-374.3***	-394.2***	1988.0***	-378.5***	26.84***	-8.524	203.9***	17.95**	-304.9***
N	291	319	121	321	324	362	182	370	325	193
R-squared	0.116	0.717	0.752	0.059	0.702	0.074	0.196	0.405	0.059	0.781

Robust Standard Errors in parenthesis; *,**,*** imply 10%, 5%, 1% significance levels, respectively.

Table 5: Timing of Technology Adoption and Financial Development: Dynamic Panel Regression

	(1) L-Electricity	(2) L-Fertilizer	(3) L-Harvest	(4) L-Irrigated	(5) L-Newspaper	(6) L-pctirrigation	(7) L-Telephone	(8) L-TV	(9) L-Tractor	(10) L-Vehicle
Lag	0.544***	0.939***	0.899***	-0.156***	0.962***	0.725***	0.417***	0.551***	0.954***	0.867***
	(0.066)	(0.029)	(0.073)	(0.033)	(0.039)	(0.032)	(0.053)	(0.055)	(0.0125)	(0.037)
Bank Credit	-0.009	-0.013*	-0.039***	-0.0004	-0.014*	-0.031***	-0.392***	-0.447***	-0.009	-0.029**
	(0.034)	(0.007)	(0.014)	(0.003)	(0.008)	(0.012)	(0.063)	(0.057)	(0.008)	(0.014)
Log of GDP	-1.44	-0.405	-0.059	-0.470	-2.425	0.025	-4.584**	2.390	0.340*	3.285**
	(1.681)	(1.306)	(2.578)	(0.487)	(1.999)	(0.018)	(2.333)	(1.489)	(0.195)	(1.467)
Primary Complete	-0.019	-0.013	-0.063*	0.002	-0.012	-0.001	-0.005	-0.056	0.004	-0.011
	(0.045)	(0.008)	(0.033)	(0.003)	(0.010)	(0.016)	(0.031)	(0.049)	(0.005)	(0.013)
Irrigatedarea		0.002	0.003							
		(0.003)	(0.004)							
Fertlizer				0.001		-0.000001			-0.012	
				(0.011)		(0.000004)			(0.018)	
2nd Order Corr	1.17(0.21)	-0.61(0.54)	-0.62(0.54)	1.06(0.29)	-1.35(0.18)	0.25(0.81)	-1.29(0.20)	1.33(0.18)	-0.05(0.27)	0.99(0.32)
Sargan	121.06(0.18)	49.2(0.67)	73.42(0.37)	29.38(0.87)	91.74(0.27)	79.23(0.32)	41.12(0.75)	59.22(0.61)	74.67(0.34)	121.29(0.17)
N	212	232	78	244	278	281	119	128	247	104

Robust Standard Errors in parenthesis; *,**,*** imply 10%, 5%, 1% significance levels, respectively

Table 6: Does Financial Development Enhance Technology Diffusion by Reducing Risk: Dynamic Panel Regression

	(1) Computer	(2) Electricity	(3) Fertilizer	(4) Harvest	(5) Internet	(6) Internet	(7) Irrigated	(8) Mobile	(9) Newspaper	(10) pctirrigated	(11) Telephone	(12) TV	(13) Tractor	(14) Vehicle_Com
Lag	0.910***	0.886***	0.559***	0.868***	0.978***	0.978***	0.863***	0.887***	0.957***	-0.00003**	0.927***	0.978***	0.686***	0.724***
	(0.031)	(0.018)	(0.087)	(0.048)	(0.026)	(0.026)	(0.032)	(0.023)	(0.016)	(0.000016)	(0.035)	(0.062)	(0.041)	(0.041)
Bank Credit	0.007**	0.013**	0.049*	0.00004*	0.041***	0.041***	0.00004*	0.201***	0.128***	0.0004***	0.036**	0.004	0.003**	-0.00002
	(0.003)	(0.006)	(0.027)	(0.00002)	(0.014)	(0.014)	(0.00002)	(0.0674)	(0.034)	(0.00002)	(0.016)	(0.044)	(0.0012)	(0.00001)
Vol GDP	-0.032*	-0.003	-0.017	-0.00001	-0.003	-0.003	0.000001	-0.397***	0.246***	0.00004	-0.040	-0.316*	0.012***	-0.0002**
	(0.017)	(0.002)	(0.060)	(0.0001)	(0.024)	(0.024)	(0.00004)	(0.136)	(0.065)	(0.00003)	(0.039)	(0.190)	(0.002)	(0.00007)
FD x RISK	0.0001**	0.0001	-0.001	0.000002	0.0005	0.0004	0.0000003	0.022***	-0.017***	0.00001***	0.002	0.009	-0.0003***	0.00001**
	(0.0004)	(0.0001)	(0.003)	(0.000006)	(0.003)	(0.0013)	(0.000002)	(0.007)	(0.003)	(0.000002)	(0.001)	(0.008)	(0.0001)	(0.000003)
Log GDP	0.509	-0.048	-1.563	0.0002	5.533***	5.533***	-0.0005	42.23***	2.753***	0.007***	1.929***	-0.820	-0.086	0.007***
	(0.443)	(0.035)	(1.622)	(0.001)	(1.804)	(1.804)	(0.0004)	(7.822)	(0.502)	(0.001)	(0.356)	(7.601)	(0.066)	(0.002)
Primary	0.0007	0.004***	-0.044**	0.00003	0.002	0.002	0.000004	0.067	-0.005	0.0001***	-0.022*	0.006	0.001	0.00002
Completion	(0.006)	(0.001)	(0.019)	(0.00006)	(0.013)	(0.012)	(0.00001)	(0.048)	(0.019)	(0.00002)	(0.011)	(0.047)	(0.0009)	(0.00001)
	-0.320				0.720*	0.720*		-0.449						
Reg. Quality	(0.225)				(0.391)	(0.391)		(1.460)						
Fertilizer													0.008***	
													(0.003)	
2nd Order Corr.	-0.49(0.62)	1.64(0.11)	0.18(0.86)	-0.09(0.93)	-1.12(0.26)	-0.76(0.87)	0.57(0.86)	0.41(0.68)	-0.53(0.59)	0.82(0.78)	-0.14(0.88)	1.37(0.17)	-1.05(0.27)	0.85(0.79)
Sargan	74.13(0. 81)	69.40(0.84)	160.13(0.53)	92.28(0.67)	83.25(0.71)	79.61(0.79)	93.57(0.73)	81.71(0.78)	92.09(0.68)	82.13(0.73)	63.78(0.87)	262.3(0.00)	71.62(0.81)	86.6(0.68)
N	226	569	233	98	328	328	286	341	281	304	191	159	231	181

Robust Standard Errors in parenthesis; *,**,*** imply 10%, 5%, 1% significance levels, respectively.

Table 7: Does Financial Development Enhance Early Timing of Technology Adoption by Reducing Risk: Dynamic Panel Regression

	(1) L-Electricity	(2) L-Fertilizer	(3) L-Harvest	(4) L-Irrigated	(5) L-Newspaper	(6) L-pctirrigation	(7) L-Telephone	(8) L-TV	(9) L-Tractor	(10) L-Vehicle
Lag	0.883***	-0.014	1.010***	0.965***	0.940***	0.930***	0.784***	0.977***	0.960***	0.933***
	(0.026)	(0.073)	(0.016)	(0.01)	(0.005)	(0.009)	(0.053)	(0.004)	(0.004)	(0.010)
Bank Credit	-0.008	-0.001***	-0.009**	-0.019***	-0.024***	-0.024**	-0.123*	-0.0009	-0.001*	-0.004
	(0.012)	(0.0002)	(0.004)	(0.007)	(0.006)	(0.009)	(0.068)	(0.004)	(0.004)	(0.011)
Vol GDP	0.035	-0.001**	-0.025	0.0194	0.033**	0.007	0.151	0.018**	0.016*	0.050*
	(0.032)	(0.0007)	(0.017)	(0.022)	(0.015)	(0.021)	(0.110)	(0.008)	(0.009)	(0.030)
FD x RISK	-0.001	0.00003	0.0007	-0.0017	-0.002**	0.0002	-0.008*	-0.0006**	-0.001*	-0.002*
	(0.002)	(0.00004)	(0.0005)	(0.0014)	(0.0009)	(0.0014)	(0.005)	(0.0003)	(0.0006)	(0.001)
Log GDP	3.554**	-0.0786***	-3.608***	0.0542	0.922***	0.799***	1.460	-0.0139	0.343***	0.639***
	(1.578)	(0.0215)	(1.025)	(0.252)	(0.176)	(0.232)	(1.337)	(0.176)	(0.108)	(0.239)
2nd Order Corr.	1.21(0.19)	0.31(0.75)	-0.08(0.93)	0.82(0.43)	-1.32(0.14)	-0.24(0.81)	-0.21(0.83)	-0.22(0.82)	-1.10(0.27)	0.94(0.34)
Sargan	94.12(0.74)	26.55(0.89)	86.03(0.76)	97.95(0.71)	74.98(0.79)	58.32(0.84)	146.57(0.99)	68.33(0.77)	79.53(0.69)	89.01(0.84)
N	487	507	244	517	563	584	403	550	518	298

Robust Standard Errors in parenthesis; *,**,*** imply 10%, 5%, 1% significance levels, respectively.

Table 8: Technology Diffusion and Interest Rate Spread: Static Panel Regression

	(1) Computer	(2) Electricity	(3) Fertilizer	(5) Harvest	(6) Internet	(7) Irrigated	(8) Mobile	(9) Newspaper	(10) pctirrigated	(11) Telephone	(12) TV	(13) Tractor	(14) Vehicle_Com
Lag	0.968***	0.447***	0.714***	0.903***	1.085***	0.650***	0.924***	1.011***	0.000002	0.943***	0.927***	0.790***	0.705***
	(0.036)	(0.024)	(0.045)	(0.019)	(0.019)	(0.036)	(0.029)	(0.013)	(0.000002)	(0.036)	(0.014)	(0.038)	(0.065)
Ir_spread	-0.014*	-0.003***	0.048	-0.0004***	-0.014	-0.0001***	-0.061	0.002	-0.0003***	-0.074**	-0.186***	-0.005	0.00005
	(0.008)	(0.00029)	(0.049)	(0.0001)	(0.031)	(0.00002)	(0.076)	(0.105)	(0.00004)	(0.036)	(0.062)	(0.006)	(0.0001)
Log GDP	1.219	-0.092***	0.037	-0.021***	4.632***	-0.003***	40.27***	-0.046**	0.038***	1.602***	8.406***	0.114*	0.014***
	(1.206)	(0.024)	(0.025)	(0.007)	(1.540)	(0.0009)	(7.893)	(0.023)	(0.002)	(0.379)	(3.078)	(0.063)	(0.004)
Pri. Complete	-0.0001	0.005	0.054***	0.0001	-0.064	0.098*	0.0002*	0.0272	0.00004*	-0.029**	0.020**	0.003	0.0001
	(0.009)	(0.006)	(0.020)	(0.0001)	(1.309)	(0.050)	(0.0001)	(0.0187)	(0.00002)	(0.013)	(0.009)	(0.002)	(0.00012)
GFCF to GDP	2.988***	0.005***			0.003						0.617		0.0005
	(1.063)	(0.001)			(0.010)						(0.705)		(0.0006)
Reg. Quality	0.286				0.220		0.246						
	(0.303)				(0.517)		(1.523)						
Irrigation			-0.0111	2.052***									
			(0.00980)	(0.764)									
2nd Order Corr.	0.41(0.68)	-0.99(0.32)	1.16(0.24)	1.33(0.19)	0.62(0.53)	-1.02(0.46)	1.03(0.46)	0.21(0.83)	-0.89(0.37)	0.07(0.94)	-1.11(0.29)	1.38(0.14)	-1.08(0.44)
Sargan	89.54(0.31)	58.63(0.75)	152.87(0.31)	52.13(0.83)	98.52(0.46)	57.73(0.79)	49.73(0.87)	79.06(0.59)	80.48(0.51)	77.65(0.62)	59.25(0.75)	91.08(0.28)	72.08(0.67)
N	163	379	236	183	388	306	220	240	200	167	431	198	196

Robust Standard Errors in parenthesis; *,**,*** imply 10%, 5%, 1% significance levels, respectively.

Table 9: Timing of Technology Adoption and Interest Rate Spread: Static Panel Regression

	(1) L-Electricity	(2) L-Fertilizer	(3) L-Harvest	(4) L-Irrigated	(5) L-Newspaper	(6) L-pctirrigation	(7) L-Television	(8) L-TV	(9) L-Tractor	(10) L-Vehicle
Lag	0.637***	0.934***	0.996***	0.974***	-0.729***	0.686***	0.668***	0.908***	0.929***	0.891***
	(0.064)	(0.014)	(0.026)	(0.011)	(0.067)	(0.042)	(0.058)	(0.018)	(0.015)	(0.025)
Ir_spread	0.050	0.046**	-0.026	0.022**	0.002	0.166**	0.295**	0.034**	0.041**	-0.006
	(0.182)	(0.019)	(0.018)	(0.009)	(0.002)	(0.074)	(0.145)	(0.015)	(0.016)	(0.029)
Log GDP	-8.793***	-0.015*	-2.635**	-0.920	-0.0005	5.892***	-5.171***	2.207***	0.592***	1.111***
	(1.922)	(0.008)	(1.189)	(0.620)	(0.0004)	(1.832)	(1.677)	(0.630)	(0.207)	(0.329)
Pri. Complete	-0.095	-0.004	-0.028	-0.025	-0.0001	-0.011	-0.115*	-0.007	-0.006	-0.034
	(0.108)	(0.007)	(0.053)	(0.077)	(0.0003)	(0.020)	(0.067)	(0.004)	(0.005)	(0.032)
GFCF/GDP	1.869***		3.653***	-0.012	-0.006		1.20e-08*	-0.807***		-1.520*
	(0.711)		(1.071)	(0.019)	(0.016)		(7.20e-09)	(0.225)		(0.878)
Irrigatedarea		0.001	-0.001							
		(0.003)	(0.002)							
2nd Order Corr.	0.48(0.63)	-1.49(0.14)	-0.22(0.83)	-1.35(0.)	-1.58(0.12)	0.06(0.95)	-1.63(0.13)	1.25(0.21)	-1.54(0.12)	-0.16(0.87)
Sargan	92.91(0.77)	79.76(0.83)	93.35(0.74)	96.19(0.63)	84.41(0.81)	84.58(0.79)	105.57(0.31)	83.17(0.82)	94.02(0.73)	99.45(0.43)
N	115	200	143	306	240	190	108	222	198	100

Robust Standard Errors in parenthesis; *,**,*** imply 10%, 5%, 1% significance levels, respectively.

Table 10: Does Level of Development Matter for Technology Diffusion: Dynamic Panel Regression

	(1) Computer	(2) Electricity	(3) Fertilizer	(4) Harvest	(5) Internet	(6) Irrigated	(7) Mobile	(8) Newspaper	(9) pctirrigated	(10) Telephone	(11) TV	(12) Tractor	(13) Vehicle_Com
Lag	0.908***	0.878***	0.559***	0.875***	0.978***	0.862***	0.887***	0.942***	-0.000003	0.929***	0.979***	0.673***	0.703***
	(0.030)	(0.018)	(0.088)	(0.052)	(0.026)	(0.032)	(0.0223)	(0.019)	(0.000002)	(0.035)	(0.062)	(0.043)	(0.042)
Bank Credit	0.007**	-0.002	0.048	0.00004*	0.040***	0.00004*	0.197***	0.127***	0.0003***	0.018	0.009	0.002	-0.00002
	(0.003)	(0.002)	(0.030)	(0.00002)	(0.014)	(0.00002)	(0.068)	(0.034)	(0.00002)	(0.017)	(0.050)	(0.001)	(0.00001)
VolGDP	-0.032*	-0.009	-0.018	-0.00001	-0.002	0.000002	-0.410***	0.234***	0.00002	-0.062**	-0.319*	0.012***	-0.0002**
	(0.017)	(0.010)	(0.060)	(0.0001)	(0.024)	(0.00004)	(0.138)	(0.065)	(0.00003)	(0.031)	(0.190)	(0.002)	(0.00007)
FD X Risk	0.0009**	0.00007	-0.002	0.000002	0.0004	0.0000003	0.023***	-0.017***	0.000004*	0.003***	0.009	-0.0003***	0.00001***
	(0.0004)	(0.00009)	(0.003)	(0.000006)	(0.0013)	(0.000002)	(0.007)	(0.0034)	(0.000002)	(0.001)	(0.008)	(0.0001)	(0.000003)
Log GDP	0.591	-0.003	-1.616	0.00004	5.658***	-0.0004	41.10***	2.367***	0.005***	1.325***	1.580	-0.135	0.004*
	(0.451)	(0.044)	(1.787)	(0.001)	(1.871)	(0.00039)	(8.021)	(0.552)	(0.0006)	(0.419)	(8.486)	(0.084)	(0.0024)
Dum_GDPPK	-0.139	-0.03*	0.054	0.0003	-0.086	-0.0002	0.862	1.206	0.009***	1.029***	-1.089	0.029	0.0017***
	(0.192)	(0.017)	(0.745)	(0.001)	(0.423)	(0.0004)	(1.293)	(0.738)	(0.0008)	(0.372)	(1.687)	(0.033)	(0.0006)
Primary	0.0014	0.008***	-0.044**	0.00003	0.002	0.000004	0.065	-0.007	0.0001***	0.028**	0.007	0.001	0.00002
Complete	(0.007)	(0.003)	(0.019)	(0.0001)	(0.013)	(0.00001)	(0.048)	(0.019)	(0.00001)	(0.012)	(0.046)	(0.0009)	(0.00006)
Reg. Quality	0.00354***				0.711*		-0.167						
	(0.00131)				(0.395)		(1.524)						
2nd Order Corr.	-0.48(0.63)	1.58(0.13)	0.17(0.86)	-0.09(0.93)	-1.13(0.26)	-1.15(0.23)	0.59(0.55)	0.48(0.63)	-1.45(0.18)	0.26(077)	-0.18(0.85)	1.35(0.18)	-0.93(0.37)
Sargan	106.20(0.54)	69.37(0.88)	129.48(0.54)	90.85(0.44)	112.37(0.36)	124.51(0.31)	92.12(0.39)	102.87(0.47)	91.74(0.41)	90.49(0.46)	82.52(0.47)	71.42(0.59)	88.31(0.41)
N	226	569	233	98	328	286	341	281	304	191	159	231	181

Robust Standard Errors in parenthesis; *,**,*** imply 10%, 5%, 1% significance levels, respectively.

Table 11: Does Level of Development Matter for Timing of Technology Adoption: Dynamic Panel Regression

	(1) L-Electricity	(2) L-Fertilizer	(3) L-Harvest	(4) L-Irrigated	(5) L-Newspaper	(6) L-pctirrigation	(7) L-Television	(8) L-TV	(9) L-Tractor	(10) L-Vehicle
Lag	0.872***	-0.012	1.007***	0.936***	0.950***	0.828***	0.781***	0.978***	0.964***	0.935***
	(0.026)	(0.074)	(0.016)	(0.021)	(0.006)	(0.014)	(0.053)	(0.004)	(0.004)	(0.011)
Bank Credit	-0.009	-0.001***	-0.009*	-0.018**	-0.017**	-0.009	-0.124*	-0.005	-0.006*	-0.004
	(0.012)	(0.0002)	(0.005)	(0.007)	(0.007)	(0.008)	(0.068)	(0.004)	(0.004)	(0.011)
Vol GDP	0.036	0.002**	-0.026	0.029	0.035**	0.048**	0.147	0.0155*	0.0168*	0.0485
	(0.031)	(0.0007)	(0.017)	(0.022)	(0.015)	(0.020)	(0.110)	(0.0083)	(0.00976)	(0.0297)
FD × RISK	-0.001	0.00003	0.0007	-0.002	-0.002**	-0.0008	-0.007	-0.0004	-0.001*	-0.002*
	(0.002)	(0.00004)	(0.0005)	(0.001)	(0.0009)	(0.0007)	(0.0046)	(0.0003)	(0.0006)	(0.001)
Log GDP	-5.071***	-0.086***	-3.771***	-2.881*	-1.026***	-8.967***	1.360	-0.524***	0.408***	-0.673***
	(1.733)	(0.025)	(1.036)	(1.652)	(0.177)	(0.987)	(1.346)	(0.096)	(0.112)	(0.249)
Dum_GDPPK	-1.072**	-0.007	-0.161	-0.403	-0.943***	-0.598*	-0.581	-0.023	-0.358**	-0.136
	(0.523)	(0.013)	(0.159)	(0.354)	(0.220)	(0.347)	(1.488)	(0.129)	(0.156)	(0.233)
2nd Order Corr.	1.26(0.24)	0.32(0.74)	-0.01(0.99)	-0.81(0.58)	-1.31(0.21)	-0.19(0.85)	0.22(0.82)	0.07(0.94)	-.91(0.36)	0.92(0.36)
Sargan	133.06(0.78)	26.19(0.91)	85.23(0.49)	65.01(0.74)	73.64(0.81)	98.72(0.42)	45.43(0.99)	63.05(0.86)	75.34(0.84)	86.92(0.45)
N	488	507	244	517	563	581	403	550	518	298

Robust Standard Errors in parenthesis; *,**,*** imply 10%, 5%, 1% significance levels, respectively.

Table 12: Technology Diffusion, Aggregate Technology Adoption Indexes: Dynamic Panel Regression

	(1) Tech_Info	(2) Tech_Info	(3) Tech_Info	(4) Tech_Info	(5) Tech_Info	(6) Agric_Tech	(7) Agric_Tech	(8) Comm_Tech	(9) Comm_Tech	(10) Comm_Tech
Lag	0.458***	0.456***	0.461***	0.810***	0.458***	0.727***	0.730***	0.932***	0.932***	0.923***
	(0.054)	(0.054)	(0.053)	(0.033)	(0.051)	(0.049)	(0.045)	(0.021)	(0.021)	(0.021)
Bank Credit	0.00194***	0.002***	0.003***	0.0023***	0.006***	0.0005**	0.0005**	0.0004*	0.0004*	0.0007***
	(0.000552)	(0.0006)	(0.0006)	(0.0005)	(0.001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Vol GDP	-0.0003	-0.0003***	-0.0004	-4.16e-11	-0.0027*	-0.0004*	-0.00043*	0.0003	-0.00027	-0.0012***
	(0.002)	(0.0001)	(0.0011)	(3.96e-11)	(0.0017)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0004)
FD × Risk	0.00001	0.000001	0.0001	0.00005	0.00003	0.00003**	0.00002**	0.00002**	0.00003**	0.0001***
	(0.00005)	(0.00005)	(0.00005)	(0.00003)	(0.0001)	(0.00001)	(0.00001)	(0.00001)	(0.000014)	(0.00002)
Log GDP	0.183***	0.182***	0.131***	0.111***	0.130***	-0.011	-0.0042	0.0099***	0.0099***	0.031**
	(0.036)	(0.036)	(0.035)	(0.020)	(0.035)	(0.014)	(0.0041)	(0.003)	(0.003)	(0.012)
Dum_GDPPK	0.0137***	0.0181***	0.013**	0.0135	0.007	0.017***	0.016***	0.009**	0.009**	0.011**
	(0.004)	(0.005)	(0.006)	(0.014)	(0.016)	(0.005)	(0.005)	(0.0046)	(0.0047)	(0.0051)
Pri. Complete	0.0004	0.0004	0.001	0.00007	0.0002	0.0001	-0.0001	0.00003	0.00003	0.000007
	(0.0006)	(0.0006)	(0.001)	(0.0001)	(0.001)	(0.0002)	(0.0002)	(0.0001)	(0.00012)	(0.0001)
Reg. Quality	0.0017**	0.0016**	0.031	0.011	0.005					
	(0.0006)	(0.0007)	(0.019)	(0.0109)	(0.004)					
2^{nd} Order Corr.	1.14(0.37)	1.38(0.19)	0.89(0.74)	1.08(0.29)	1.23(0.26)	0.09(0.93)	0.09(0.92)	0.26(0.81)	0.39(0.69)	0.39(0.70)
Sargan	78.59(0.76)	82.21(0.68)	91.66(0.58)	79.68(0.74)	97.22(0.52)	88.44(0.63)	89.58(0.62)	90.83(0.61)	96.46(0.52)	96.51(0.54)
N	334	334	334	598	346	234	234	257	257	258

Robust Standard Errors in parenthesis; *,**,*** imply 10%, 5%, 1% significance levels, respectively.