Does Education Influence Clean Tech Venture Capital and Private Equity Exits in Africa?

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May 1, 2013

Abstract

Using a novel dataset, I investigate whether education in post-match general partner and portfolio company teams influences clean-tech venture capital and private equity exits in Africa. The evidence suggests that relative to write-offs, the probability of clean-tech initial public offerings increases with an increasing proportion of bachelors degrees but decreases with an increasing proportion of masters degrees and graduates from top-ranked universities. The probability of clean-tech trade sales increases with an increasing proportion of masters or doctoral degrees and graduates from top-ranked universities but decreases with an increasing proportion of bachelors degrees. Finally, the probability of clean-tech secondary sales increases with an increasing proportion of masters degrees and graduates from top-ranked universities but decreases with an increasing proportion of bachelors or doctoral degrees.

Keywords: private equity; venture capital; clean-tech; renewable energy; human capital; Africa

JEL classification: J24, G24, O55, Q42

1 Introduction

In 2010, the clean technology (clean-tech) energy industry comprising of biofuels, wind power, solar and fuel cell industries generated $188.1 billion in global revenues. This represented a 30.2 percent increase compared to 2009 (Pernick et al., 2011). Responding to this opportunity, limited partners (LPs) increased their portfolio allocations to venture capital and private equity investments, not only in clean energy but in other clean-tech[1] industries as well (Satyamurthy et al., 2010).[2] Beyond LPs' private benefits, positive externalities arise from increased energy access and security, as well as health benefits from a cleaner environment.[3] Therefore, successful outcomes from these investments are desired and understanding whether human capital can play a role in achieving these outcomes is interesting.

The main objective of this article is to investigate whether post-match education in general partner (GP) and portfolio company teams influences clean-tech venture capital and private equity outcomes. According to Spence (1973), education is a signal of a team's underlying ability. Assuming that teams with more ability have better outcomes, I expect that education in post-match GP and portfolio company teams should be positively related to better clean-tech outcomes, where these outcomes are measured by the probability of exit via initial public offering (IPO), trade sale, or secondary sale, relative to a write off.[4] I use a novel dataset of venture capital or private equity exits across African countries from 1995 to 2012 to investigate whether this relationship occurs.

[1]Clean-tech investments occur in the agriculture, air and environment, materials, energy, recycling and waste, manufacturing and industry, transportation, water, and wastewater industries (*see* National Advisory Council for Environmental Policy and Technology (2008) for examples in each industry.)

[2]Venture capital and private equity investments are made by GPs, who are intermediaries that directly invest in privately held portfolio companies through funds using equity or quasi-equity instruments. They actively manage these investments as advisors, directors, or managers; with an explicit strategy to exit in the medium term (Sahlman, 1990). GPs obtain the money to invest from LPs, who are institutional investors such as pension funds and university endowments. While wealthy individuals (angel investors) use their own money to directly finance privately held portfolio companies, they will not be included in this article due to lack of data on their activities.

[3]These issues have increased scholarly interest in the clean-tech research agenda (Edenhofer et al., 2012; Wüstenhagen and Menichetti, 2012).

[4]Types of exit include: IPOs through new listings on stock exchanges; trade sales involving acquisitions by a larger firm or portfolio companies repurchasing stakes, secondary sales where GPs sell their stakes to another GP, but the portfolio company does not sell; and write-offs involving liquidations (Cumming and Johan, 2008)

To identify the relationship I use a multinomial logit specification of clean-tech exits with non-innovative (traditional) sector exits as an additional control. The choice to invest in clean-tech requires GPs to forgo venture capital and private equity opportunities in traditional sectors. These foregone opportunities should have relatively higher chances of exit because they are more familiar and have a higher level of market acceptance compared to clean-tech initiatives (Wüstenhagen et al, 2007).[5] Compared to the traditional sector exits, which face the lowest acceptance barriers and have the highest level of familiarity, we can expect the probability of clean-tech exits to be lower because they have a relatively lower level of acceptance and familiarity. I also investigate if the effect of education on clean-tech outcomes is significantly different from other-tech outcomes, which may face similar market acceptance barriers.[6]

In summary, the evidence suggests that relative to exits from traditional investments and write-offs, an increase in the proportion of bachelors (graduates from a top-ranked university and masters) degrees in a post-match GP and portfolio company team increases (decreases) the probability of clean-tech IPO exits. It also suggests that an increase in the proportion of graduates from a top-ranked university and masters or doctoral (bachelors) degrees in a post-match GP and portfolio company team increases (decreases) the probability of clean-tech trade sale exits. Finally, the evidence suggests that an increase in the proportion of graduates from a top-ranked university and masters (bachelors or doctoral) degrees in a post-match team increases (decreases) the probability of clean-tech secondary sale exits. However, these results are not significantly different from other-tech exits.

The rest of the article is organized as follows. Section 2 reviews related literature. Section 3 discusses the method and data used to achieve the article's objective. Section 4 presents the results and a discussion. The last section summarizes and draws conclusions based on the results.

[5] Acceptance is distinguished as socio-political, community, or market acceptance (Wüstenhagen, 2007)

[6] Other-tech includes biotechnology, information and communication technology, and microfinance sectors, or in activities that involve cutting edge manufacturing techniques.

2 Literature Review

Venture capital and private equity markets are characterized by weak information where GP and portfolio company teams rely on signals e.g. education, to attain an equilibrium (Spence, 1973; Hoppe et al., 2009; Kushnir, 2010).[7] To the extent that these education signals reflect agents' underlying abilities, they represent the pre-match potential that each agent has to contribute to post-match success. Defining education in post-match teams as the treatment effect, a better quality treatment should result in better outcomes. Therefore, the predicted relationship is that *post-match GP and portfolio company teams with more education should achieve better outcomes (exits).*

Among previous empirical studies that have investigated the effect of human capital on venture capital and private equity outcomes, Dimov and Shepherd (2005) find that while a GP team's education is positively related to venture capital IPO exits, its work experience is negatively related to the proportion of write-offs.[8] Zarutskie (2010) finds that while a GP team's venture capital or private equity industry work experience and start-up experience are positively related to the proportion of a portfolio exited via IPO or trade sale, teams with more MBA degrees have a lower proportion of exits.

While these previous empirical studies indicate that human capital is important, they do not focus on clean-tech outcomes. Those that do find that other-tech companies outperform clean-tech companies (Boulatoff and Boyer, 2009). However, they also find that clean tech companies perform no worse than their conventional (non clean-tech) energy counterparts (Ng and Olowojolu, 2010). In addition, they find that investors' experience, defined as the number of years they state that they have in the renewable energy sector, is positively related to the share of these investments in a portfolio, but negatively related to investment performance, defined as investors' perceptions of whether

[7] Education represents general human capital that is defined as skills acquired through formal education, which can be applied across most firms and settings (Zarutske, 2010).

[8] Work experience captures industry-specific human capital that is defined as skills specific to a particular time or setting, which is learned in prior jobs or industries and are transferable to future jobs (Zarutske, 2010).

their portfolio performance is above, equal to, or below a competitor's performance (Mansini and Menichetti, 2012).

However, the previous studies that focus on clean-tech outcomes only provide evidence from publicly held firms. Boulatoff and Boyer (2009) compare the financial performance of 310 public, clean-tech companies to their other-tech counterparts listed on the NASDAQ financial market. Ng and Olowojolu (2010) compare the operational performance, stock performance and the ability to raise finance by 99 public clean-tech energy companies to their conventional energy counterparts between 2004 and 2009.[9] In addition to not distinguishing between publicly or privately held portfolio companies, Mansini and Menichetti's (2012) definition of investors is not limited to GPs, but also includes banks, utilities, pension funds, hedge funds, insurance companies, private engineering companies, etc.

Finally, the datasets used in the empirical studies outlined above are limited to North America or Europe. Dimov and Shepherd's (2005) dataset consists of venture capital exits in the wireless communication industry in 2002 for 112 independent US GPs.[10] Zarutskie's (2010) dataset consists of venture capital exits by 318 first-time funds of independent GPs established in the USA between 1980 and 1998 (regardless of industry). Mansini's and Menichetti's (2012) dataset consists of clean-tech energy investments by 96 European investors in 2009.

The key contribution of this article will be to determine whether education in post-match GP or portfolio company teams influences clean-tech exits for privately held firms and whether this influence is significantly different for other-tech exits. Evidence from a sample of exits in Africa contributes to the broader empirical literature on venture capital and private equity by providing insights from a region where current knowl-

[9]They measure operational performance by gross margin, return on assets and return on equity; stock performance by average five-year stock return, standard deviation of average five-year stock return and average five-year stock return versus the average five-year NASDAQ composite index return; and ability to raise finance by five-year growth in equity, five-year growth in cash flow from financing activities and five-year growth in total liabilities.

[10]Independent GPs are not majority-owned by governments or multilateral agencies acting on their behalf (public), banks or insurance companies (finance), or corporations. However, they raise funds from these institutions.

edge is descriptive e.g summary statistics (Jones and Mlambo, 2009; Sathyamurthy et al., 2010), case studies (Masum et al., 2010), or limited to single-country studies (Hassan, 2010; Hassan and Ibrahim, 2012).[11]

3 Methods & Data

To determine whether education influences clean-tech venture capital or private equity outcomes, I rely on a static reduced form empirical model. This section discusses the model, the data it relies on, and the strategy used to estimate it.

3.1 Empirical Model

The model used to investigate the predicted relationship stated in the previous section adopts the linear additive form specified in Equation 1.

$$y_{gpct} = \alpha + X'_{gpct}\beta_1 + \Gamma'_{gpct}\beta_2 + \varepsilon_{gpct} \tag{1}$$

Where y_{gpct} is the dependent variable. α denotes the constant term. X_{gpct} is a matrix containing variables reflecting the average of the proportion of post match education traits that are shared between GP ($g = 1...G$), and portfolio company ($p = 1...P$) teams, in a market that is represented by a country ($c = 1...C$), in a certain year ($t = 1...T$).[12] I am interested in estimating the coefficient vector β_1. Γ_{gpct} is a matrix of control variables that includes post-match shared non-human capital, and unshared time varying characteristics specific to the country in which exits occur. ε_{gpct} denotes the remaining random error term.

[11] So far, multi-continent venture capital and private equity studies have ignored Africa. Those that do not, only include South Africa (Cumming and Johan, 2009).

[12] I use the average as opposed to the product of their traits to prevent eliminating the presence of a trait in a matched pair if one agent has it while the other agent doesn't. For example, if 0.35 of a GP's team has a masters degree while none of a portfolio company's team has this education trait, the average of their shared trait will be 0.175 $[(0.35+0) \div 2]$ while the product would be 0 (0.35×0).

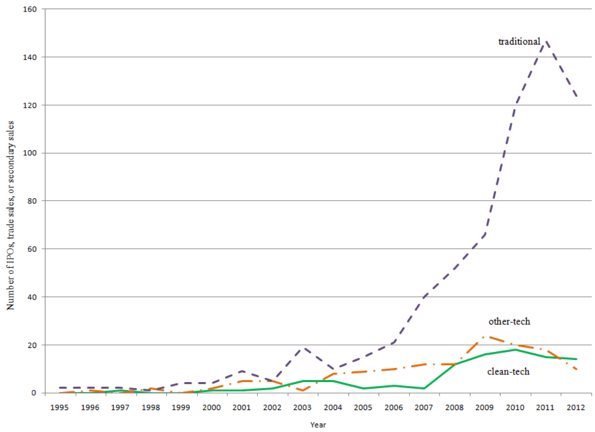
Table 1: Summary statistics

Variable	mean	standard deviation	minimum	maximum	observations
y (= 1 to 4)	2.8554	0.8944	1	4	3104
bachelors	0.6182	0.2341	0.0095	1	860
masters	0.2887	0.2034	0	1	834
doctorate	0.0508	0.0968	0	0.5698	831
certification	0.3443	0.1786	0	0.8	712
top-ranked university	0.1929	0.1659	0	0.8214	540
age (in years)	20.1181	18.1646	0	118.5	1999
Portfolio company:					
clean-tech (=1 if yes)	0.1039	0.3052	0	1	3435
other-tech (=1 if yes)	0.1936	0.3952	0	1	3435
traditional (=1 if yes)	0.7025	0.4572	0	1	3435
Market:					
GDP growth rate per capita	0.0294	0.0187	-0.0622	0.1084	3440
clean-tech usage	0.0272	0.0112	0	0.1161	3384
kyoto (= 1 if ratified)	0.8188	0.3853	0	1	3471
country_id	42.7141	7.5958	3	53	3473
year_exit	2007.64	2.6825	1995	2012	2848

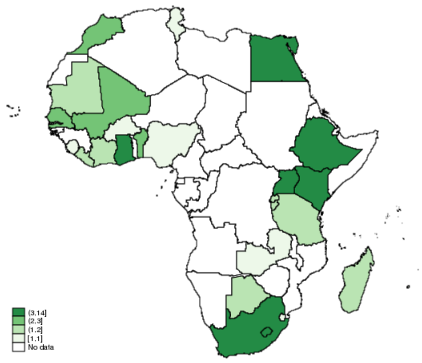
3.2 Data

The data on venture capital and private equity exits and the education traits of GP and portfolio company teams are obtained from various public, secondary sources including audited annual reports and unaudited sources e.g. website content, conference presentations, press releases, and newsletters. This data is summarized in Table 1.

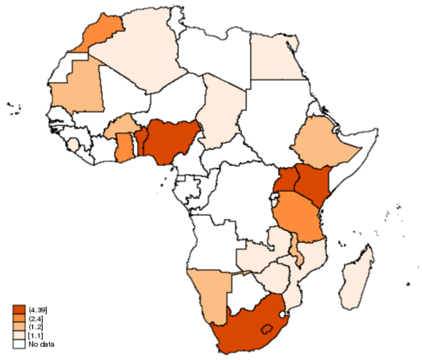
The data capturing the characteristics of countries where exits occur are obtained from the publicly accessible, online data portal provided by the World Bank (2013). This portal includes information from the African Development Indicators, Doing Business, Governance Indicators, World Development Indicators, and Global Development Finance databases. The data are reported by government agencies, obtained through field surveys, or compiled from other agencies e.g. the International Monetary Fund, United Nations, and World Economic Forum. These data are also summarized in Table 1. I discuss them in more detail in the rest of this sub-section.



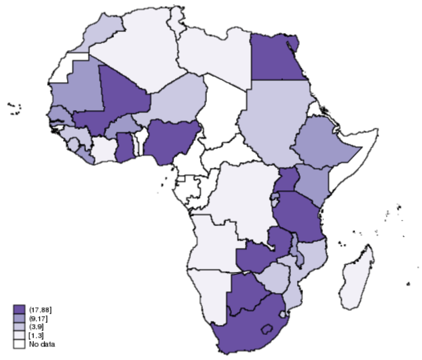
Number of IPO, trade sale, or secondary sale exits



Note: Clean-tech exits = 81



Note: Other-tech exits; n = 104



Note: Traditional exits; n = 556

Figure 1: Venture capital and private equity exits in Africa (1995 - 2012)

3.2.1 Dependent variable

The dependent variable is a categorical indicator equal to one if the exit from a match is a write-off (the baseline category), two if it is a secondary sale, three if it is a trade sale, and four if it is an IPO.[13] It represents a random sample of exits by 194 GPs from 741 portfolio companies across 45 countries, which are illustrated in Figure 1.[14] 26 of these GPs exited from 81 clean-tech portfolio companies over the sample period.

[13] I cannot assess outcomes using the internal rate of return (IRR) because the data on this metric result in a sample size that is inadequate for analysis.

[14] The top-left panel of Figure 1 illustrates that although the overwhelming majority of venture capital and private equity exits in Africa occur in the non-innovative traditional sector, clean-tech exits on the continent have risen since 2007 and had caught up with other-tech investments by 2010.

3.2.2 Key independent variable

The variable of interest is the average proportion of education in post-match GP and portfolio company teams. It includes the proportion of a team's members with a bachelor, masters or doctoral degree. It also includes the proportion of a team's members that have obtained post-graduation industry certifications e.g. certified public accountant, certified financial analyst, executive education, etc. Finally, it includes the proportion of a team's members that graduated from a top-ranked university.[15]

For the GP, I only include team members whose job title is chief executive officer, director, investment or fund manager, investment officer, principal, partner, associate, or analyst.[16] I exclude non-executive directors and chairpersons of a GP because they are more likely to be involved in board responsibilities to LPs. I also exclude team members responsible for executing deals on other continents rather than in Africa. Finally, I exclude support staff because they are likely to be focused on in-house administration.

I define the start and departure dates of a GP's or portfolio company's team member as the year they joined or left the team. These dates are explicitly indicated in the annual reports, member profiles on a GP's or company's website, or are issued in press releases. In cases where this information was not provided from these sources, I relied on LinkedIn, Bloomberg, or Zoominfo.[17] If the departure dates were unavailable even from these sources, I defined it as the last year they appeared in an annual report or the year prior to which they are announced to have joined a new GP or portfolio company.

[15] The universities include Brown, Columbia, Cornell, Dartmouth, Duke, Harvard, Massachusetts Institute of Technology, University of California-Berkeley, University of Chicago, University of Pennsylvania, Princeton, Yale, and Stanford in the USA; McGill and University of Toronto in Canada; Cambridge, Oxford, Imperial College, London School of Economics and London Business School in the UK; Sorbonne University in France; Bocconi University in Italy; Tilburg University in the Netherlands; University of New South Wales in Australia; Tsinghua University in China; and University of Cape Town, University of Witwatersrand, and University of Stellenbosch in South Africa.

[16] Since not all these team members interact with a specific portfolio company, the results can be interpreted as an upper bound.

[17] Using these sources, I also identified past employees that were part of current team members' social networks. This allowed me to mitigate measurement error for the education traits of GP and portfolio company teams.

3.2.3 Controls

I include age as a non-human capital trait shared between GP and portfolio company teams. I measure it using the difference between the year an exit occurs and their year of establishment.

The non-human capital traits specific to a portfolio company include three separate binary indicators equal to one if a portfolio company is clean-tech, other-tech, or traditional, and zero otherwise.[18]

The country characteristics that I include are real GDP per capita growth rate in purchasing power parity terms with a base year of 2005. I also include the percentage of alternative and nuclear energy in total energy use in each country. A higher value of this measure should reflect higher market acceptance that should have a positive influence on clean-tech exits. Furthermore, I include a binary indicator equal to one if a country has ratified the Kyoto Protocol, and zero otherwise (United Nations, 2012).[19]

3.3 Estimation Strategy

I adopt a multinomial logit estimation strategy where I include clean-tech and other-tech exits separately (with traditional exits as a control group), without distinguishing portfolio companies by investment stage. This multinomial logit determines whether education in a post-match GP and portfolio company teams' influences IPOs, trade sales, and secondary sales, respectively (with write-offs as the baseline category).

I then calculate the difference between the results of clean-tech and other-tech estimations. To determine whether these differences are significant, I estimate a single regression that includes both types of portfolio companies. Its independent variables include the education traits and their controls interacted with the clean-tech or other-tech binary indicator.

[18]These are required for dataset restrictions that categorize portfolio companies by type.

[19]Using a panel dataset covering 26 OECD countries from 1991–2004, Popp et al. (2011) find that ratification of the Kyoto Protocol plays an important role for clean-tech energy adoption.

4 Results & Discussion

In this section I present multinomial logit estimation results and discuss them by exit type. While write-offs are not a desired exit for GPs and portfolio companies, I also present and discuss the results of this type of exit for completeness. I will limit the discussion to the marginal effects.

4.1 Initial Public Offering

The first row in Table 2 illustrates the effect of bachelor degrees on IPO exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of bachelor degrees in a post-match GP and portfolio company team increases the probability of a clean-tech IPO exit by 0.9314 and is significant at the 1% level. Column 4 illustrates that a one unit increase in the proportion of bachelor degrees in the post-match team increases the probability of an other-tech IPO exit by 0.6479 and is also significant at the 1% level. Finally, column 6 illustrates that a one unit increase in the proportion of bachelor degrees in a post-match GP and portfolio company team increases the probability of a clean-tech, relative to other-tech, IPO exit by 0.2385 (0.9314 - 0.6479) but is not significant even at the 10% level.

The third row in Table 2 illustrates the effect of masters degrees on IPO exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of masters degrees in a post-match GP and portfolio company team decreases the probability of a clean-tech IPO exit by 0.8587 and is significant at the 1% level. Column 4 illustrates that a one unit increase in the proportion of masters degrees in the post-match team decreases the probability of an other-tech IPO exit by 0.399 and is also significant at the 1% level. Finally, column 6 illustrates that a one unit increase in the proportion of masters degrees in a post-match GP and portfolio company team decreases the probability of a clean-tech, relative to other-tech, IPO exit by 0.4597 (-0.8587 - -0.399) but is not significant even at the 10% level.

Table 2: Multinomial logit results for Education: Initial Public Offerings

	Clean-Tech		Other-Tech		(1) - (3)	(2) - (4)
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
bachelors	21.4644	0.9314***	16.7700***	0.6479***	4.6944	0.2835
	(13.8603)	(0.1109)	(5.2411)	(0.1016)		
masters	26.3606	-0.8587***	6.3042	-0.3990***	20.0564	-0.4597
	(20.0157)	(0.1758)	(5.8128)	(0.1492)		
doctorate	-62.9976**	-0.7982*	-48.4955***	-1.6294***	-14.5021	0.8312
	(28.0862)	(0.4370)	(9.2294)	(0.4292)		
certification	17.3209	0.1559	11.5459**	-0.0222	5.775	0.1781
	(10.6309)	(0.1089)	(5.6220)	(0.1179)		
top-ranked university	-40.4060*	-0.8489***	-24.2076***	-0.8881***	-16.1984	0.0392
	(24.3279)	(0.1664)	(5.3059)	(0.1484)		
Observations	375		399		430	
Prob > chi2	0.0000		0.0000		0.0000	
Pseudo R^2	0.5744		0.4286		0.6448	

Note: Controls for clean-tech exits include age, clean-tech, GDP growth per capita, clean-energy use, and kyoto; Controls for other-tech exits include age, other-tech, and GDP growth per capita;
Delta standard errors are in parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

The fifth row in Table 2 illustrates the effect of doctoral degrees on IPO exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of doctoral degrees in a post-match GP and portfolio company team decreases the probability of a clean-tech IPO exit by 0.7982 and is significant at the 10% level. Since this is not significantly different from a write-off, I do not discuss how it differs from other-tech IPO exits. Column 4 illustrates that a one unit increase in the proportion of doctoral degrees in the post-match team decreases the probability of an other-tech IPO exit by 1.6294 and is significant at the 1% level.[20]

The seventh row in Table 2 illustrates the effect of post-degree certifications on IPO exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of certifications in a post-match GP and portfolio company team increases the probability of a clean-tech IPO exit by 0.1559 but is not significant even at the 10%

[20] Across all exit types, except write-offs, the marginal effect for this education trait is greater than 1. This could be due to the low prevalence of doctoral degrees among GP or portfolio company teams in Africa.

level. Column 4 illustrates that a one unit increase in the proportion of certifications in the post-match team decreases the probability of an other-tech IPO exit by 0.0222 but is also not significant even at the 10% level. Since the effect of an increase in the proportion of certifications is not significantly different between IPOs and write-offs for both clean-tech and other-tech, I do not discuss how they differ.

The ninth row in Table 2 illustrates the effect of graduation from a top-ranked university on IPO exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of graduates from a top-ranked university in a post-match GP and portfolio company team decreases the probability of a clean-tech IPO exit by 0.8489 and is significant at the 1% level. Column 4 illustrates that a one unit increase in the proportion of graduates from a top-ranked university in the post-match team decreases the probability of an other-tech IPO exit by 0.8881 and is also significant at the 1% level. Finally, column 6 illustrates that a one unit increase in the proportion of graduates from a top-ranked university in a post-match GP and portfolio company team increases the probability of a clean-tech, relative to other-tech, IPO exit by 0.0392 (-0.8489 - -0.8881) but is not significant even at the 10% level.

In summary the findings suggest that an increase in the proportion of bachelors (graduates from a top-ranked university and masters) degrees in a post-match GP and portfolio company team increases (decreases) the probability of a clean-tech IPO exit. However, these results are not significantly different from other-tech exits.

4.2 Trade sale

The first row in Table 3 illustrates the effect of bachelor degrees on trade sale exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of bachelor degrees in a post-match GP and portfolio company team decreases the probability of a clean-tech trade sale exit by 0.4803 and is significant at the 1% level. Column 4 illustrates that a one unit increase in the proportion of bachelor degrees in the post-match team decreases the probability of an other-tech trade sale exit by 0.5260 and is

Table 3: Multinomial logit results for Education: Trade Sale

	Clean-Tech		Other-Tech		(1) - (3)	(2) - (4)
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
bachelors	11.2980	-0.4803***	10.2059**	-0.5260***	1.0921	0.0457
	(13.8916)	(0.0962)	(5.1954)	(0.1019)		
masters	35.0408*	0.2984**	6.3986	-0.2448*	28.6422	0.5432
	(20.0809)	(0.1373)	(5.7127)	(0.1275)		
doctorate	-41.0904	1.9438***	-20.8277**	3.0907***	-20.2627	-1.1469
	(27.7438)	(0.2658)	(8.3713)	(0.2622)		
certification	16.2256	-0.0331	12.6307**	0.2038*	3.5949	-0.2369
	(10.6998)	(0.1052)	(5.6124)	(0.1094)		
top-ranked university	-32.1224	0.3590***	-16.0853***	0.5757***	-16.0371	-0.2167
	(24.3500)	(0.1368)	(5.1189)	(0.1319)		
Observations	375		399		430	
Prob > chi2	0.0000		0.0000		0.0000	
Pseudo R^2	0.5744		0.4286		0.6448	

Note: Controls for clean-tech exits include age, clean-tech, GDP growth per capita, clean-energy use, and kyoto;
Controls for other-tech exits include age, other-tech, and GDP growth per capita;
Delta standard errors are in parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

also significant at the 1% level. Finally, column 6 illustrates that a one unit increase in the proportion of bachelor degrees in a post-match GP and portfolio company team increases the probability of a clean-tech, relative to other-tech, trade sale exit by 0.0457 (-0.4803 - -0.5260) but is not significant even at the 10% level.

The third row in Table 3 illustrates the effect of masters degree on trade sale exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of masters degrees in a post-match GP and portfolio company team increases the probability of a clean-tech trade sale exit by 0.2984 and is significant at the 5% level. Column 4 illustrates that a one unit increase in the proportion of masters degrees in the post-match team decreases the probability of an other-tech trade sale exit by 0.2448 but is only is significant at the 10% level. Since this is not significantly different from write offs, I do not discuss how it differs from clean-tech trade sale exits.

The fifth row in Table 3 illustrates the effect of doctoral degrees on trade sale exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of doctoral degrees in a post-match GP and portfolio company team increases the probability of a clean-tech trade sale exit by 1.9438 and is significant at the 1% level. Column 4 illustrates that a one unit increase in the proportion of doctoral degrees in the post-match team increases the probability of an other-tech trade sale exit by 3.0907 and is also significant at the 1% level. Finally, column 6 illustrates that a one unit increase in the proportion of doctoral degrees in a post-match GP and portfolio company team decreases the probability of a clean-tech, relative to other-tech, trade sale exit by 1.1469 (1.9438 - 3.0907) but is not significant even at the 10% level.

The seventh row in Table 3 illustrates the effect of post-degree certifications on trade sale exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of certifications in a post-match GP and portfolio company team decreases the probability of a clean-tech trade sale exit by 0.0331 but is not significant even at the 10% level. Column 4 illustrates that a one unit increase in the proportion of certifications in the post-match team increases the probability of an other-tech trade sale exit by 0.2038 but is only significant at the 10% level. Since the effect of an increase in the proportion of certifications is not significantly different between trade sales and write-offs for both clean-tech and other-tech, I do not discuss how they differ.

The ninth row in Table 3 illustrates the effect of graduation from a top-ranked university on trade sale exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of graduates from a top-ranked university in a post-match GP and portfolio company team increases the probability of a clean-tech trade sale exit by 0.3590 and is significant at the 1% level. Column 4 illustrates that a one unit increase in the proportion of graduates from a top-ranked university in the post-match team increases the probability of an other-tech trade sale exit by 0.5757 and is also significant at the 1% level. Finally, column 6 illustrates that a one unit increase in the proportion of graduates from a top-ranked university in a post-match GP and portfolio company team decreases the probability of a clean-tech, relative to other-tech, trade sale exit by 0.2167 (0.3590 - 0.5757) but is not significant even at the 10% level.

In summary the evidence indicates that an increase in the proportion of graduates from a top-ranked university and masters or doctoral (bachelor) degrees in a post-match GP and portfolio company team increases (decreases) the probability of a clean-tech trade sale exit. However, these results are not significantly different from other-tech exits.

4.3 Secondary sale

The first row in Table 4 illustrates the effect of bachelor degrees on secondary sale exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of bachelor degrees in a post-match GP and portfolio company team decreases the probability of a clean-tech secondary sale exit by 0.3477 and is significant at the 1% level. Column 4 illustrates that a one unit increase in the proportion of bachelors degrees in the post-match team decreases the probability of an other-tech secondary sale exit by 0.0034 but is not significant even at the 10% level. Since this is not significantly different from write offs I do not discuss how an increase in bachelor degrees affects clean-tech, versus other tech, secondary sale exits.

The third row in Table 4 illustrates the effect of masters degrees on secondary sale exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of masters degrees in a post-match GP and portfolio company team increases the probability of a clean-tech secondary sale exit by 0.729, and is significant at the 1% level. Column 4 illustrates that a one unit increase in the proportion of masters degrees in the post-match team increases the probability of an other-tech secondary sale exit by 0.7105 and is also significant at the 1% level. Finally, column 6 illustrates that a one unit increase in the proportion of masters degrees in a post-match GP and portfolio company team increases the probability of a clean-tech, relative to other-tech, secondary sale exit by 0.0185 (0.729 - 0.7105) but this is not significant even at the 10% level.

Table 4: Multinomial logit results for Education: Secondary Sale

	Clean-Tech		Other-Tech		(1) - (3)	(2) - (4)
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
bachelors	12.2548	-0.3477***	13.8854***	-0.0034	-1.6306	-0.3443
	(13.9258)	(0.1027)	(5.2659)	(0.0971)		
masters	39.8290**	0.7290***	12.9395**	0.7105***	26.8895	0.0185
	(20.1100)	(0.1341)	(5.8257)	(0.1183)		
doctorate	-73.7033**	-1.4805***	-53.1774***	-1.7648***	-20.5259	0.2843
	(28.4897)	(0.4358)	(9.7908)	(0.4318)		
certification	16.3671	-0.0264	11.2832**	-0.0655	5.0839	0.0391
	(10.6991)	(0.0913)	(5.6558)	(0.1039)		
top-ranked university	-32.8350	0.2755**	-19.3944***	0.1339	-13.4406	0.1416
	(24.3765)	(0.1269)	(5.2979)	(0.1231)		
Observations	375		399		430	
Prob > chi2	0.0000		0.0000		0.0000	
Pseudo R^2	0.5744		0.4286		0.6448	

Note: Controls for clean-tech exits include age, clean-tech, GDP growth per capita, clean-energy use, and kyoto; Controls for other-tech exits include age, other-tech, and GDP growth per capita;
Delta standard errors are in parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

The fifth row in Table 4 illustrates the effect of doctoral degrees on secondary sale exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of doctoral degrees in a post-match GP and portfolio company team decreases the probability of a clean-tech secondary sale exit by 1.4805 and is significant at the 1% level. Column 4 illustrates that a one unit increase in the proportion of doctoral degrees in the post-match team decreases the probability of an other-tech secondary sale exit by 1.7648 and is also significant at the 1% level. Finally, column 6 illustrates that a one unit increase in the proportion of doctoral degrees in a post-match GP and portfolio company team increases the probability of a clean-tech, relative to other-tech, secondary sale exit by 0.2843 (1.4805 -1.7648) but this is not significant even at the 10% level.

The seventh row in Table 4 illustrates the effect of post-degree certifications on secondary sale exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of certifications in a post-match GP and portfolio company team decreases the probability of a clean-tech secondary sale exit by 0.0264 but is not significant even at the 10% level. Column 4 illustrates that a one unit increase in the proportion of certifications in the post-match team decreases the probability of an other-tech secondary sale exit by 0.0655 but is also not significant even at the 10% level. Since the effect of an increase in the proportion of certifications on clean-tech or other-tech secondary sale exits is not significantly different from write-offs, I do not discuss how they differ.

The ninth row in Table 4 illustrates the effect of graduation from a top-ranked university on secondary sale exits, relative to writeoffs. Column 2 illustrates that a one unit increase in the proportion of graduates from a top-ranked university in a post-match GP and portfolio company team increases the probability of a clean-tech secondary sale exit by 0.2755 and is significant at the 1% level. Column 4 illustrates that a one unit increase in the proportion of graduates from a top-ranked university in the post-match team increases the probability of an other-tech secondary sale exit by 0.1339 but is not significant even at the 10% level. Since this is not significantly different from write-offs I do not discuss how it differs from clean-tech secondary sale exits.

In summary the evidence indicates that an increase in the proportion of graduates from a top-ranked univerity or masters (bachelors or doctoral) degrees in a post-match GP and portfolio company team increases (decreases) the probability of a clean-tech secondary sale exit.

4.4 Write-offs

The first row in Table 5 illustrates the effect of bachelor degrees on write-offs. Column 1 illustrates that a one unit increase in the proportion of bachelor degrees in a post-match GP and portfolio company team decreases the probability of a clean-tech write-off by 0.1034 but is not significant even at the 10% level. Therefore, I do not discuss how an increase in this education trait affects clean-tech, versus other tech, write-offs. Column 2 illustrates that a one unit increase in the proportion of bachelors

Table 5: Multinomial logit results for Education: Write-offs

Variable	Clean-Tech (1) Marginal Effect	Other-Tech (2) Marginal Effect	(1) - (2) (3) Marginal Effect
bachelors	-0.1034	-0.1185***	0.0151
	(0.0729)	(0.0486)	
masters	-0.1687	-0.066	0.1027
	(0.1176)	(0.0548)	
doctorate	0.3349*	0.3035***	0.0314
	(0.1720)	(0.1000)	
certification	-0.0964	-0.1161**	0.0197
	(0.0602)	(0.0580)	
top-ranked university	0.2144	0.1785***	0.0359
	(0.1388)	(0.0543)	
Observations	375	399	430
Prob > chi2	0.0000	0.0000	0.0000
Pseudo R^2	0.5744	0.4286	0.6448

Note: Controls for clean-tech exits include age, clean-tech, GDP growth per capita, clean-energy use, and kyoto; Controls for other-tech exits include age, other-tech, and GDP growth per capita; Delta standard errors are in parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

degrees in the post-match team decreases the probability of an other-tech write-off by 0.1185 and is significant at the 1% level.

The third row in Table 5 illustrates the effect of masters degrees on writeoffs. Column 1 illustrates that a one unit increase in the proportion of masters degrees in a post-match GP and portfolio company team decreases the probability of a clean-tech write off by 0.1687 but is not significant even at the 10% level. Column 2 illustrates that a one unit increase in the proportion of masters degrees in the post-match team decreases the probability of an other-tech write-off by 0.066 but is also not significant even at the 10% level. Since the effect of an increase in the proportion of this education trait on clean-tech or other-tech write-offs is not significant, I do not discuss how they differ.

The fifth row in Table 5 illustrates the effect of doctoral degrees on writeoffs. Column 1 illustrates that a one unit increase in the proportion of doctoral degrees in a post-match GP and portfolio company team increases the probability of a clean-tech write-off by 0.3349 and is significant at the 10% level. Since I cannot rely on this level of significance as evidence, I do not discuss how an increase in this education trait affects clean-tech, versus other tech, write-offs. Column 2 illustrates that a one unit increase in the proportion of doctoral degrees in the post-match team increases the probability of an other-tech write-off by 0.3035 and is significant at the 1% level.

The seventh row in Table 4 illustrates the effect of post-degree certifications on writeoffs. Column 1 illustrates that a one unit increase in the proportion of certifications in a post-match GP and portfolio company team decreases the probability of a clean-tech write-off by 0.0964 but is not significant even at the 10% level. Therefore, I do not discuss how an increase in this education trait affects clean-tech, versus other tech, write-offs. Column 2 illustrates that a one unit increase in the proportion of certifications in the post-match team decreases the probability of an other-tech write-off by 0.1161 and is significant at the 5% level.

The ninth row in Table 4 illustrates the effect of graduation from a top-ranked university on writeoffs. Column 1 illustrates that a one unit increase in the proportion of graduates from a top-ranked university in a post-match GP and portfolio company team increases the probability of a clean-tech write-off by 0.2144 but is not significant even at the 10% level. Therefore, I do not discuss how an increase in this education trait affects clean-tech, versus other tech, write-offs. Column 2 illustrates that a one unit increase in the proportion of graduates from a top-ranked university in the post-match team increases the probability of an other-tech write-off by 0.1785 and is significant at the 1% level.

5 Summary & Conclusion

This article aims to determine whether education in post-match GP and portfolio company teams influences clean-tech venture capital and private equity exits in Africa and if this influence significantly differs from other-tech exits.

The evidence suggests that relative to exits from traditional investments and write-offs, an increase in the proportion of bachelors (graduates from a top-ranked university and masters) degrees in a post-match GP and portfolio company team increases (decreases) the probability of clean-tech IPO exits. It also suggests that an increase in the proportion of graduates from a top-ranked university and masters or doctoral (bachelors) degrees in a post-match GP and portfolio company team increases (decreases) the probability of clean-tech trade sale exits. Finally, the evidence suggests that an increase in the proportion of graduates from a top-ranked university and masters (bachelors or doctoral) degrees in a post-match team increases (decreases) the probability of clean-tech secondary sale exits. However, these results are not significantly different from other-tech exits.

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