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"Building Markets from Ethnically Fractionalized Networks:

Recruiting New Investors into Kenya's Nairobi Stock Exchange"

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Building Markets from Ethnically Fractionalized Networks: Recruiting New Investors into Kenya’s Nairobi Stock Exchange

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Despite low incomes, weak property rights, low levels of financial literacy, and an ethnically diverse population, the number of domestic investors in Kenya’s Nairobi Stock Exchange increased almost ten-fold to 1.4 million between from 2006 to 2008, with 98% of all new investors entering the market via seven IPOs. This paper models the diffusion of the practice of shareholding through Kenyan society as a process of social contagion, with social networks based on ethnic and geographic homophily carrying information about the profitability of previous investments from current to potential investors. I study the effect of geographically clustered ethnic groups on the national-level diffusion of this new economic practice in two ways. First, I consider how local levels of ethnic homogeneity affect a node’s susceptibility to network contagion. Second, I consider how contagion flows through two separate network spaces measured by geographic and ethnic distance between existing and potential adopters of the practice. I merge investor-level data from the NSE’s electronic trading platform to national survey data to construct a unique database showing the timing of first share purchase, town of residence and profits earned on IPO investments for 83% of all Kenyan investors as well as town-level estimates of Kenya’s ten primary ethnic populations and a range of town-level characteristics. After controlling for IPO-specific effects and a comprehensive set of structural characteristics of each town, I find strong evidence that the positive contagion effect of profits earned by geographically proximate peers is sharply reduced in ethnically homogeneous communities and that ethnic networks operate above and beyond geographic proximity between current and potential adopters as significant transmitters of material information and therefore recruiters of new investors. The policy implications for constructing functional capital markets in developing countries are discussed.

INTRODUCTION
A growing sociological literature studies the global diffusion of market institutions, such as free trade zones (Duina 2006), independent central banks (Polillo & Guillén 2005), and the creation of stock exchanges in developing countries (Weber, Davis, and Lounsbury 2010). Henisz, Zelner, 1

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1 I am grateful to Rose Mambo (CEO) and James Gikonyo (Director of Information Technology) of the Central Depository and Settlement Corporation for making available the data used in this analysis. I also thank Sammy Muvelah, Kwame Owino, Raphael Owino, and the Institute for Economic Affairs- Nairobi for their assistance and ongoing support. Helpful comments on earlier drafts were provided by Matthew Bothner, Benjamin Cornwell, Donald Palmer, David Strang, Richard Swedberg and seminar participants at Cornell University, The Wharton School, and the University of Maryland. All remaining errors are my own. Financial support was provided by the National Science Foundation (Grant No. 0802469) as well as several Cornell University organizations: Center for the Study of Economy and Society, Einaudi Center for International Studies, Center for the Study of Inequality, and Graduate School International Research Fund.
& Guillén (2005) analyze a range of market-oriented reforms (privatization, regulatory autonomy, and market liberalization) from the perspective of neoinstitutional and world systems theory, focusing on the combined influence of coercion, normative emulation, and competitive mimicry in state-level policy adoption. Weber, Davis, and Lounsbury (2010) employ a similar theoretical lens to study the role played by coercion and mimicry but extend the scope of the inquiry to include the longer term performance of these nascent market institutions, finding that the number of listed firms and total market capitalization of newly established stock exchanges is negatively linked to creation of stock exchanges via coercive forces and positively related to normative emulation in the adoption process.

This paper extends our understanding of market building processes in two ways. First, I study the within-country diffusion of a new market practice, providing the first quantitative analysis of how participation in state-created neoliberal practices spreads through a society. Second, I extend social network analysis by considering how contagion spreads through networks with high degrees of population-level ethnic diversity that manifest as highly homogeneous local ethnic clusters. More specifically, this paper studies the construction of a nascent financial market in a challenging environment by pursuing two specific questions about how profits earned by earlier investors is transmitted to potential investors: 1) Does high levels of local ethnic homogeneity affect a community’s susceptibility to material information from its geographic peers?; 2) What are the relative contributions of networks based in geographic versus ethnic proximity in spreading information about new, profitable opportunities?

Diffusion scholars and organization theorists have long studied how performance of previous adopters influences later adoption (e.g. Rao 1994; Conell & Cohn 1995) and how shared traits, including cultural similarities, between network contacts further influences the spread of a practice (e.g. Lincoln, Gerlach & Takahashi 1992; Greve 1998; Terlaak & Gong 2008). Many of these studies implicitly address search processes, where actors seeking solutions to known problems place a higher value on information gathered from similar others (Strang and Meyer 1994). This search process has been especially explored in terms of cultural similarities, with several researchers studying how networks of co-ethnics aid the search process for immigrant entrepreneurs (Aldrich & Waldinger 1990; Portes & Sensenbrenner 1993; Kalnins & Chung 2006). This paper takes a different approach to the role played by ethnic ties in the diffusion of information by studying how nodes in a network may be insulated from understanding new opportunities available in the economy as a result of being located in ethnically homogeneous geographic areas clusters or being situated a greater distance from ethnically similar others. Instead of assuming that actors seek information about investing, I assume that potential investors in developing countries are uninformed about the practice and model the extent to which they are introduced to it and convinced that it is potentially beneficial based on attributes of their local environment.

My theoretical approach similarly expands the literature on ethnic fractionalization in the field of development economics. Scholars in this literature study the effects of ethnic diversity on economic development, focusing on the causal mechanism that ethnic differences retard support for public spending programs that would benefit the country to a greater degree than
private spending (see Posner 2004 for a comprehensive review; Alesina and La Ferrera 2005; Easterly, Ritzen, and Woolcock 2006). Methodologically, I advance this literature in the same way as the sociological literature on the state-level diffusion of neoliberal reform policies by considering the effects of within-country concentrations of ethnic populations on market formation. Studying local participation in imported institutional arrangements is sympathetic to Easterly's (2008) argument that the successful implementation of imported policies often depends on bottom-up receptiveness by the domestic population to newly created practices. The policy implications of understanding the recruitment of new investors can scarcely be underestimated, as policy analysts have noted that many emerging stock exchanges fail to mobilize and allocate nascent capital and create more liquid trading environments in large part because they fail to attract a sufficient level of investor participation (Bishop 1988; Sing 1997; Yartey & Adjasi 2007). Similarly, the need to mobilize domestic capital rather than rely on attracting foreign capital is evidenced by the fact that most emerging markets receive only slight levels of foreign capital while a few, larger emerging markets attract the lion’s share of foreign investment (Moss, Ramachandran & Standley 2007; Kenny & Moss 1998).

The paper proceeds as follows. The next section provides a description of the empirical setting in Kenya. The section that follows develops two research questions that address how material information about the profits earned by previous investors diffuses to potential investors, considering how levels of local ethnic homogeneity may insulate a community from network influence and how information might travel differently through networks situated in geographic versus ethnic space. A section describing the unique data and methods used to explore these questions are followed by results of the quantitative analysis. A concluding discussion explores theoretical contributions for diffusion theorists and policy makers as well as generalizability of the findings and future research directions.

**Empirical Setting: The Rise of Retail Shareholding in Kenya**

The Nairobi Stock Exchange (NSE) was established in 1954 by British colonial businessmen who sold shares of their Kenya-based enterprises to a select group of fellow colonialists (for a more complete history of the NSE see Kimura & Amoro 1999; Ngugi 2003). African Kenyans were prohibited from participating in the exchange until after independence in 1963, but neither the end of colonial constraints nor a consultancy by the United States Agency for International Development (USAID) to modernize the exchange in the late 1980s succeeded in stimulating shareholding among average Kenyans. In fact, the NSE was called “a stock exchange in name only” by the head of the USAID delegation in 1988, who concluded that the lack of competition among buyers and the low numbers of total investors distorted share prices, reduced trading volume and liquidity, and ultimately inhibited the NSE from mobilizing individual savings (Bishop 1988).

Figure 1 shows the total number of shareholders, the timing of all initial public offers, and the performance of the exchange as measured by the NSE20 Index since 1980. Despite numerous listings of new firms and a world-best rate of return of 187% in 1994, the total number of shareholders in the NSE remained constant at approximately 50,000 after the end of USAID’s
involvement in 1990 until the privatization of Kenya Airways in 1996 which doubled the number of investors to 100,000.²

Prior to 2006, newly floated shares on the NSE were priced relatively high and sold in large lots to a small group of pension funds, government officials, and stockbrokers serving Kenyan elites (Ngugi 2003). Barriers to entry for small-scale shareholders were directly addressed in the Privatization Act of 2005, passed by the Kenyan Parliament in that year as part of a larger package of economic liberalization reforms.³ With the goal of better utilizing the domestic stock exchange to mobilize nascent domestic capital and increase liquidity in the market by recruiting more investors, the Act formally required that any firm listing on the NSE must make the floated shares available to at least 1,000 shareholders. The Act also required regulatory approval of key features of each initial public offer (IPO), including the initial share price to be charged, the minimum number of shares to be purchased by each IPO investor, and the allocation of IPO shares across retail and institutional investors and employees of the listing firm. With share prices fixed, minimum buy-ins held low, and allocation policies controlled by the regulator, the state effectively forced listing firms to allocate a high percentage of IPO shares to smaller retail investors who could buy in affordable lots.⁴

The state quickly followed the passage of the Privatization Act in 2005 with an aggressive privatization program, in which several select state-owned and private firms were listed on the stock exchange. The use of privatization IPOs to deepen capital markets, both in terms of the number of total investors and the number of listed firms, is a common strategy in developing countries, and almost all emerging markets make use of some form of politicized offer terms (Jones et al 1999; Boutchkova & Megginson 2000). The Privatization Act of 2005 clearly served as a catalyst in attracting more investors to the market, as the total number of investors on the NSE increased ten-fold between mid-2006 and late 2008.

Although the long term trend of adopting the practice of shareholding seen in Figure 1 resembles the s-shaped diffusion curve associated with exponential hazard rates resulting from the cascading effects of contagion by previous adopters (Schelling, 1978; Coleman, Katz & Menzel 1966; Rossman 2010), Figure 2 shows that adoption occurs in discrete, punctuated periods followed by longer spells of dormancy. These discrete periods are initial public offers of

² Few formal records of the numbers of investors in each firm exist prior to 2004. The numbers of shareholders prior to that year are estimated based on accounts found in the annual reports of the NSE, the Capital Markets Authority, and estimates provided by Kenyan fund managers.

³ The passage of the Privatization Act of 2005 followed notable other events in Kenyan politics, including the election of a pro-business administration in 2002 and the publication of the Ndungu Land Report in 2004 that called into question the legal ownership status of a large amount of land. Both of these represent shifts in the Kenyan political landscape in the lead up to the growth in participation on the NSE. A more complete discussion of these events is beyond the scope of this paper, which focuses on variation in adoption of shareholding given these political circumstances.

⁴ The use of such politicized offer terms is common in emerging markets, where states adopt listing requirements that incentivize participation by retail investors. For a more in-depth review of the practice, see Jones et al. (1999).
newly listing firms, and more than 98% of all new investors enter the NSE via subscription to an IPO. Figure 2 also shows that IPOs differ significantly in their ability to attract new investors. New investors do not seem to be increasingly recruited via cascade effects of prior adopters, as evidenced by the fact that the first, third, and sixth IPOs attract the most new investors. Other IPOs recruit relatively few new investors, suggesting that characteristics of IPO events should be a prominent part of an investigation of the recruitment of new investors in Kenya.

**Figure 2 about here**

Figure 3 shows two maps marking the locations of Kenyan investors who owned shares prior to the passage of the Privatization Act in 2005 and the locations investors as of December 2008; the number of investors in each town is represented by dots of increasing size. Figure 4 demonstrates that the growth of shareholding from 140,000 investors in late 2005 to 1.4 million at the end of 2008 was accomplished mostly by a deepening participation rates in a relatively small number of towns rather than expanding the number of locations in which investors live; a 900% growth in the practice of shareholding was accompanied by a 54% increase in the number of unique towns in which investors reside. Figure 3 therefore demonstrates strong a priori reasons to approach the spread of retail shareholding as a contagion process.

**Figure 3 about here**

For a number of reasons, Kenya is an unlikely setting for such an explosion of retail investing activity. Per capita income in Kenya in 2006 was just below the international poverty line of US$2 per day, while real average earnings declined in 2005 and held steady in 2006 due to high inflation (Kenya NBS 2007: 11, 89). At the start of the boom in retail investing in 2006, less than 25% of the total population made use of any formal sector financial product such as a bank account, line of consumer credit, insurance policy or pension fund (FSD-Kenya 2006).

Institutional economists have long argued that the strength of a country’s property rights regime is a key indicator of participation in financial markets (La Porta, Lopez-de-Salinas, & Shleifer 1997). If this argument holds in Kenya we would expect low levels of participation in the NSE. The World Bank’s 2009 Investor Protection Index ranks the Kenyan state as one of the weaker protectors of investors’ property rights, ranking 81st internationally. In their daily activities, average Kenyans have an even worse experience with Kenya’s various rent seeking bureaucracies. Ranking 150th worldwide in Transparency International’s 2007 Bribery Perception Index, 87% of Kenyans reported paying bribes for basic services.

In addition to the formal institutions, informal social institutions are also a possible source of friction for stimulating collective participation in Kenya’s emerging stock exchange. Of particular interest in this area is the degree of ethnic heterogeneity, as Kenya is home to 42 distinct tribal ethnicities and a history of troubled relations between them. The failed 2007 presidential election is a stark example of the schisms between tribal groups, as the largest and most economically dominant tribe was accused by a coalition of smaller tribes of rigging the
election, resulting in a near civil war in which more than 1,300 people were killed. This tragic episode is currently the focus of an International Criminal Court trial, where six leaders from several tribal groups are charged with crimes against humanity for coordinating and funding attacks against members of rival tribes. At the root of these tensions is access to and possession of economic resources, a key element found by sociologists to determining rates of ethnic entrepreneurship (Aldrich & Waldinger 1990). Economists have studied the effects of ethnic heterogeneity on economic development, finding that high levels of ethnic fractionalization negatively affect domestic economic growth (Easterly & Levine 1997), as well as provision of public goods required for development (Alesina & La Ferrara 2005).

GEOGRAPHY, ETHNICITY, AND SOCIAL CONTAGION
Paradoxically, sociologists and organization theorists might predict that the above litany of institutional weaknesses might in fact encourage Kenyans to see share ownership as a legitimate activity, so long as it is perceived to be compatible with individual goals of material gain (Rogers 2003). Yenkey (forthcoming) argues that shareholding in Kenya is framed as an aspirational activity, with share ownership advertised as a rare opportunity to experience class mobility. The deleterious effects of low incomes and high levels of corruption, for example, could be outweighed by desires to take advantage of rare opportunities to increase wealth, even if those opportunities are not well understood or inconsistent with prevailing practices. In this section, I outline two research questions that address the role played by intrinsic characteristics of towns, proximity to previous investors, and how ethnic homogeneity mediates social contagion.

My focus on individual-level, demand side adoption of shareholding leads me away from world systems-oriented mechanisms of coercion, emulation, and mimicry used to understand state-level adoption of neoliberal institutions (e.g. Henisz, Zlemer & Guillén 2005; Weber, Davis & Lounsbury 2010) and toward a focus on social learning between individuals linked by network structures. Learning from the experiences of previous adopters is understood to be a rational process, allowing potential adopters to judge the efficacy of new, uncertain practices based on the experiences of prior adopters (Banerjee 1992; Strang and Meyer 1993). For example, Rao (1994) demonstrates that early U.S. automobile manufacturers recruited more consumers as a result of their vehicle’s strong results in performance trials. Similarly, Conell and Cohn (1995) show an increased incidence of strikes among French coal miners following earlier strikes that achieved workers’ goals. Holden’s (1986) study of the likelihood of airline hijackings based on the perceived success of earlier strikes and hijackings comes to similar conclusion. Hedstrom (1998) labels this behavior “rational imitation,” whereby actors mimic earlier actions of others when the behavior is seen to fit her interests.

Figure 4 shows indexed share prices (listing price = 100) for each of the first six IPOs at the time of the start of the next IPO. Share prices are shown only so far as the number of trading days until the next IPO subscription period begins, as shown on the horizontal axis. Price gains in these recent Kenyan IPOs range from a high of 330% to a low of -45%. Shares in two of the six IPOs trade at less than their listing price at the start of the next IPO, and there is a high degree of variation across the four that trade in positive territory at the start of the next IPO.
Ethnic homogeneity and susceptibility to network contagion

These profits experienced by earlier investors constitute the “infectious” material information that is to be spread to potential adopters (Strang and Tuma 1993). The relevant question, however, is how does this information spread through a population that is unfamiliar with the practice? Studies of the spread of practices based on physical proximity have long been a part of diffusion research (e.g. Hagerstrand 1967; Spilerman 1970; Land, Deane & Blau 1991; Hedstrom 1994). Network scholars continue to incorporate the effects of physical proximity, highlighted by the formation of long distance ties between venture capital firms (Sorenson & Stuart 2001) and the geographic distribution of new firms related to IPO events (Stuart & Sorenson 2003). To borrow Podolny’s (2001) metaphor, geographic proximity networks serve as pipes through which information about the financial benefits of share ownership travel through the society. The first research question I studies how local ethnic homogeneity might serve as a blockage in these pipes, restricting the flow of material information to potential investors.

Economists and political scientists have recently addressed similar questions in studies of the effects of ethnic fractionalization on economic development in emerging market countries. Here, researchers find that social cleavages resulting from ethnic diversity lead to high degrees of localized orientation, such that preferences form for private, local spending projects to the detriment of more national-level, collective goods that facilitate economic development but are seen as also benefitting rival ethnic groups (see Easterly 2001 for a review). Alesina and La Ferrera (2005) posit that countries with ethnically fragmented populations will increasingly prefer private, localized consumption orientations rather than public, market-oriented systems. Collier (2000) finds a similar outcome, with ethnic heterogeneity resulting in a wider variation in preference for public goods, resulting in lower ability of the state to satisfy all constituents and therefore providing fewer public goods. Easterly, Ritzen, and Woolcock (2006) investigate the effects of social cohesion on the formation of more stable institutions that facilitate economic growth, defining social cohesion in terms of cleavages along which divisions within a society might emerge, such as the ethnic divisions that characterize Kenyan society.

The literature on ethnic fractionalization rests largely on cross-national, comparative studies of macro-level outcomes predicted by national measures of ethnic diversity. The causal mechanism, however, is cohesion within ethnic groups, and it is this cohesion that results in political support for local spending projects. Incorporating sociological insights on group-level processes has the potential to deepen our theoretical understanding of this process by investigating geographically clustered ethnic groups and their likelihood of being recruited into a collective market structure as a result of susceptibility to network influence. If we consider the extent to which localized groups are attuned to the world around them, it is possible to theorize about how locally homogeneous groups are susceptible to network influence.

For example, Merton (1949) discussed the different world views of two groups, locals and cosmopolitans, with locals being town residents that attend mainly to information and activities
occurring within the community and cosmopolitans regarding themselves to be more “citizens of the world,” with a strong interest in learning from external peers.

A causal mechanism underlying Merton’s idea of locals and cosmopolitans is later postulated by network theorists, with Coleman (1988, 1990) stipulating that closed social networks act as a source of productive social capital by creating a dense, local network in which information is more readily available and monitoring is more effective, thus increasing trust (for a more comprehensive review, see Burt 2000). In this way, a denser local network could result in higher proportions of locals, producing a negative effect on market formation due to network closure stimulated by highly homogeneous ethnic communities that are less susceptible to outside influence.

Research Question 1: Are communities characterized by higher degrees of ethnic homogeneity less susceptible to the contagious influence of earlier profits earned by geographically proximate peers, and thus less likely to contribute more new investors into the market?

Contagion through geographic versus ethnic networks
Strang and Tuma (1993) discuss how shared attributes between previous and potential adopters affect susceptibility to network-based contagion, and Strang and Meyer (1993) theorize that diffusion should face less resistance between actors who share a similar culture. Aldrich and Waldinger (1990) find that social networks between co-ethnics increases the flow of information about resources required for business ventures, ostensibly reducing the reliance of a dense ethnic network of sufficient size on peer provided information. Similarly, Portes and Sensenbrenner (1994) argue that immigrants make use of ethnic networks to access information about job opportunities, and Kalnins & Chung (2006) find the same in their study of immigrant hotel entrepreneurs. Organizational scholars have produced a range of results demonstrating that managers engage in vicarious learning, whereby they consider not just the outcomes experienced by other firms but also the traits of the previous adopter as a way of more precisely estimating their own likelihood of success, as success by similar others is considered more relevant than the experiences of dissimilar others (Terlaak & Gong 2008; Greve 1998). While organization theory provides a tractable starting point for studying the role of ethnicity in social networks, these literatures are built around questions about search processes; often the research setting is one in which actors encounter problems, material or perceived, and they survey similar others to find suitable solutions. While information gathered may be evaluated relative to perceived shared traits between actors, the search process is more or less rationally agentic from the beginning.

The recruitment of investors into a nascent market, however, is more likely to be a case where uninformed potential investors are made aware of the advantages or disadvantages of a newly available practice by previous adopters without themselves searching out information about the practice. Even after the dramatic rise in participation in the national stock exchange in the three previous years, half of all Kenyans reported having never heard of the Nairobi Stock Exchange in 2008 (FSD Kenya 2009). I argue that adjudicating the performance of earlier profits experienced in the Kenyan stock market is not a search process engaged in by actors seeking
new opportunities. Instead, news of earlier profits comes to actors via social linkages, and a deep sociological literature provides reasons how these linkages arise and their ability to serve as effective “pipes.”

Homophily has long been the causal mechanism for network tie formation (see McPherson, Smith-Lovin, & Cook for a review), with physical proximity and ethnic similarity being two of the most powerful homophily-inducing traits. Ethnicity, and more specifically race, has been found to influence a range of ties, including friendships (Shrum et al 1988), confidants and discussion partners (Marsden 1987, 1988; Schneider et al 1997), and marriage (Kalmijn 1988). Physical proximity is also a foundational attributes affecting tie formation (Zipf 1947; Gans 1968; see McPherson, Smith-Lovin, & Cook for a review). This literature provides a robust causal mechanism for understanding how actors come to form ties, through which information and influence might flow. I am not, however, able to measure the extent of ties between members of different ethnic groups in Kenya, and therefore I cannot stipulate a precise causal mechanism that explains why the influence of profits earned by members of other ethnic groups might be stronger or weaker.

No previous research that I am aware of considers the simultaneous contributions of physical and ethnic ties in the dissemination of material information. Without a priori reasons to expect one type of network link to take primacy over another, I let the data provide quantification of the contribution of ethnic versus geographic networks in the diffusion of material information on past profits and the recruitment of new investors into this market. The purpose of this paper is not to predict participation in the formal economy by any one particular ethnic group, despite evidence presented above that such groups do exist in Kenya in the form of unique tribes. Instead, I make use of the ethnic diversity in Kenya to study the extent to which ethnic dissimilarity operates similar to geographic distance in the dissemination of material information and therefore market construction.

**Research Question 2: What are the relative contributions of geographic versus ethnic proximity networks in recruiting new investors by spreading information about profits earned by earlier investors?**

**Controls for intrinsic characteristics of investors and firms**

Although not hypothesized, a wide range of structural elements have been shown to contribute to capital market participation and therefore must be controlled for if the influence of ethnic and geographic proximity is to be reliably studied. One of the first control measures must be the financial ability to purchase shares. A large body of research in organizational literature demonstrates that willingness to adopt risky innovations increases when an actor performs under the level to which they aspire (Kahneman & Tversky 1979; Greve 1998), while managers whose firms exceed expectations exhibit more risk adverse behaviors (March & Shapira 1987). At the individual level, sociologists have long shown that economically disadvantaged groups are increasingly risk loving in games of chance precisely because the activity is seen as a rare way to release pressures that accrue to lower social classes as well as providing an opportunity structure in which economic resources may be accrued (Devereux 1949; Frey 1984). The
theoretical argument that lower income groups participate in national lotteries for these reasons has been empirically verified (King 1985; Beckert and Lutter 2009). These bodies of work suggest that low income areas in Kenya may be more or less likely to participate in a new practice seen to be both risky but also potentially profitable.

Related to levels of individual income, research has linked prior experience with formal financial products to higher levels of financial literacy (Braunstein and Welch 2002), and lower levels of financial literacy to lower participation rates in stock markets in the U.S. (van Rooij, Lusardi, and Alessie 2007). Earlier work by anthropologists, however, suggests that populations in developing countries demonstrate high degrees of sophistication in informal financial arrangements (Guyer 1985) and in abilities to construct market exchange arrangements (Ensminger 1996), suggesting that a lack of formal financial sector participation might not be as much of a hindrance to shareholding as might be expected by observers unfamiliar with the emerging market context.

Net of the effects of income and experiences with other formal financial technologies, it is common for ethnic groups to have differing access to resources that foster participation in the formal sector economy (Aldrich & Waldinger 1990). In Kenya, the Kikuyu are the largest of 42 tribes, comprising 21% of the total population. Members of this tribe were favored by British colonial business interests due to a perception of their stronger sense of Western business ideals (Wrong 2008), and the Kikuyu inherited many of the economic and political institutions from the British at the time of independence in 1963 (Himbara 1994). The Kikuyu continue to be regarded as the most entrepreneurial tribe in Kenya (Ndemo 2005) and have the strongest presence in formal economy. 596 firms with membership in the Kenya Association of Manufacturers in 2007, 25 are headquartered in districts with majority Luhya populations, 10 are headquartered in districts with majority Luo populations, and the remaining 561 are in districts where Kikuyu comprise the dominant ethnic population. These disparities stand in a stark contrast to the relatively close population sizes, with the the Kikuyu, Luhya, and Luo representing approximately 18, 15, and 13% of the total population, respectively.

In addition to attributes of potential investors, characteristics of listing firms may account for a large proportion of investor demand. Figure 2 above shows that the three IPOs that recruit the largest number of new investors were privatizations or divestitures of state owned firms. Privatization events are often responsible for recruiting the largest numbers of new investors in emerging markets (Boutchkova & Megginson 2000; Lieberman & Kirkness 1988). Public desire to purchase shares in divested state-owned firms is related to earlier work by political scientists that suggests that post-independence African populations are likely to see ties to the state as a source of wealth and class mobility (Sklar 1979; Diamond 1987), a feature that Yenkey (forthcoming) argues increases demand for IPO shares in privatizing parastatals.

Firms listing on the NSE also vary considerably in their use of advertising campaigns to recruit investors during IPOs. A number of studies demonstrate the effects of advertising campaigns on capital market performance suggest that advertising plays a strong role in generating interest in and returns to firms during initial public offers. Grullon, Kanatas, and Weston (2004) argue that
product market advertising has a positive spillover into firms’ capital market operations. Similarly, Pollock and Rindova (2003) study the media as an “institutional infomediary” that “render some firms more comprehensible and desirable, and therefore more legitimate” (p. 631) in the eyes of investors. Positive effects of media coverage include higher initial share prices and increased turnover in early secondary trading.

DATA AND METHODS
I study the above research questions using a unique, individual-level dataset showing the timing of first share purchase for all 1.4 million Kenyan domestic investors. The NSE migrated to an electronic platform in November 2004, and since that time all trades have been routed through a central server; there is no over the counter market. Since the inception of the electronic platform all trading activities, including IPO share subscriptions, require an investor to have an electronic account. Kenyan law stipulates that only one account is allowed for each individual or company, enforced by the requirement of providing a national identity card or articles of incorporation for individuals and companies, respectively. Therefore, I assume that each electronic account represents a unique investor. Access to the NSE’s electronic platform shows not only the timing of first share ownership for each investor but also all subsequent share trades as well as individual background data for each investor including town of residence. 83% of NSE accounts contain a verifiable town of residence, and the 17% whose location is unverified show no patterns suggesting self-reporting bias. Based on these towns of residence, I merge town-level estimates of ethnic populations and a range of town-level control variables gleaned from three recent nationally representative surveys: the 2005 Kenya Household Integrated Budget Survey (KBS 2006) and the 2006 and 2009 waves of the FinAccess Survey, a survey conducted by Financial Sector Deepening-Kenya in partnership with the World Bank that collects information about the use of a wide range of formal and informal financial products.

Geographic and ethnic proximity networks
The analysis makes use of two distinct networks measures, one situated in physical space and one dependant on ethnic differences between towns. Geographic distance between towns, measured in kilometers, is computed automatically using ArcGIS software. Ethnic distance between towns is measured using Lieberson’s (1969) measure of qualitative variation:

\[ EthnicDist = 1 - \left( \sum_{z=1}^{10} (p_{iz} \times p_{jz}) \right) \]  

Where there are \( k = 10 \) possible ethno-linguistic groups in each town and \( p_{iz} \) represents the proportion of town \( i \) that belongs to ethno-linguistic group \( z \) and \( p_{jz} \) represents \( z \)'s population in town \( j \). Equation 1 produces a single measure of ethnic distance between all pairs of towns that is the probability that if you choose one member of each town at random, the pair will be from different ethnic groups. My method for estimating the ethnic composition of each town is described below.

Following standard practice in network analysis (Burt 1987; Burt & Carlton 1989; Bothner 2003), I assign a weight to all alters according to their proportional distance in the network,
with that distance measured in geographic or ethnic space, with weights of all alters to a given ego summing to unity:

\[ w_{ij} = \frac{\left[ \max_{k=1}^{563} (d_{ik} - d_{ij}) \right]^\nu}{\sum_{k=1}^{563} \left[ \max_{k=1}^{563} (d_{ik} - d_{ij}) \right]^\nu} \quad (2) \]

\( K \) is the set of all 563 towns in the sample, so that \( \max (d_{ik}) \) is the ego-defined maximum distance from town \( i \) to any other town in the sample and \( d_{ij} \) is the distance from ego to a particular alter within the set \( K \). \( \nu \) is a user-defined term affecting the relative weight of more spatially proximate alters. Values for \( \nu \) much larger than one signify that ego is influenced primarily by closely proximate alters, while fractional values for \( \nu \) suggest that ego is influenced by contact with a wide range of alters, regardless of proximity. Following Burt (1987), I recognize that it is not knowable at the outset the degree to which ego receives information from alters of various proximity; therefore, it is unclear what values of \( \nu \) are appropriate in this setting. Models are estimated using a range of \( \nu \) values and I discuss empirical evidence supporting higher values of \( \nu \).

**Dependent Variable**

*Number of new investors.* Because I do not have complete background data for each investor, I shift the unit of analysis to the town-IPO event. The dependent variable is a count of new investors in each town whose first ownership of shares occurs as a result of subscribing for shares in each IPO that has taken place on the NSE since the passage of the Privatization Act in 2005. More than 98% of all new investors first enter the market via a subscription to one of these seven IPOs. The subscription period for each IPO varies from as short as ten days to as long as five weeks, during which time all investors visit the office of an intermediary (a stock brokerage or licensed agent thereof) and pays for all subscribed shares in advance. If it is the first time an individual is buying shares, she must open an NSE account. I measure the count of new investors as those that receive shares for the first time rather than account openings because there are approximately 120,000 CDSC accounts that were opened but which never took a deposit of a single share. The dependent variable does not distinguish between investors according to size of initial investment or registration as individuals or companies.

**Explanatory Variables**

*Town profit.* Performance of previous investments is a town-level measure of the total, nominal value of paper profits earned on investments made in the previous IPO. Profits are calculated based on share prices at the end of trading on the day prior to the start of the subscription period for the next IPO and are expressed in tens of millions of Kenyan Shillings. Any investor who sold her shares prior to that time is assigned the selling share price as the basis for calculating the return.

*Profits of geographic and ethnic peers.* Profits earned in all geographically and ethnically proximate towns in the previous IPO are constructed as a single measure of the sum of profits made in all other towns in the network weighted according to their proportional proximity to ego using equation (2) above:
Where \( k \) represents a single measure on the set of all alter towns to any ego \( i \), comprised of \( J=562 \) other towns in the sample.

Town’s ethnic composition. The proportion of each town’s population belonging to each of ten ethno-linguistic groups is estimated from district-level aggregates taken from the 2006 and 2009 waves of the FinAccess Survey. Respondents choose to complete the survey in one of the ten most common languages and tribal dialects used in Kenya. Survey administrators note the language used and the proportions of respondents using each language are then aggregated to the district-level. I estimate town-level measures according to the scheme described below.

Ethnic homogeneity. Local ethnic homogeneity is measured as a location quotient, defined as the local proportion of a given ethnic group relative to its proportion of the national population (Brown & Chung 2006).

Control variables

Advertising exposure. Data on exposure to IPO advertising campaigns was obtained from a Nairobi-based market research firm that tracks advertisements on all radio and television stations and print media outlets. Firm researchers note the time of day, duration, and other features of each advertisement in each media outlet and use those characteristics to estimate its retail value. Actual price paid for each ad is not known (larger advertisers may negotiate bulk prices for advertisements, for example), but the estimated retail price is a better measure of advertising exposure because it provides a standardized measure of the volume of expected advertising exposure for residents of each town. Estimated retail price of all advertisements for each of the seven IPO firms over a four month period prior to listing are available for each of Kenya’s 42 radio stations. Radio advertising is the most reliable measure of exposure to IPO advertising, as radio is the most widespread form of media consumed in Kenya and an average of 80% of IPO advertising budgets are dedicated to radio campaigns. Geographic footprints of radio stations are well defined, allowing for the creation of measures of the level of radio advertising each Kenyan town is exposed to in each IPO. Survey data on listenership of each radio station in each district, provided by the market research firm, is used to weight the exposure of advertisements on each radio station.

Number of previous adopters in the town. Mimicry, in the form of conformity to popular practice, is controlled for by including a count of the number of investors in each town that invests in the previous IPO (Tolbert & Zucker 1983). Alternative measures of previous adopters

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5 This version of the analysis makes use of the location quotient rather than a Herfindal or Shannon Index due to the fact that the town-level estimates of ethnic populations used are based on district-level aggregates, as described below. Estimating town-level population characteristics based on district-level data yields variation at the local level that calls into question Herfindal and Shannon Index measures. Future data collection efforts that might make these alternative measures of local agglomeration possible are discussed in the conclusion.
were also estimated, including the lagged number of new investors and the total number of
town residents who owned shares at any previous time, without affecting model estimates.

**Town wealth.** Survey administrators for the 2005 Kenya Integrated Household Budget Survey
noted the condition of each dwelling in which respondents live. I use this data to generate
estimates of the proportion of town populations that are high, medium, and low socio-
ecconomic status. Any dwelling with a dirt floor is coded as low SES; high SES households are
characterized by an improved roof and floor as well as piped water and flush toilet; medium SES
households are any that fall between these two categories.

**Experience with formal financial products.** Town-level measures of prior experience with other
financial products are constructed from the 2006 and 2009 waves of the FinAccess Survey.
Experience with formal financial products is measured as the percentage of the town reporting
having used any formal financial product, consisting of bank accounts, credit or debit cards,
insurance policies, or pension funds, at any previous time.

**Town’s at risk population and geographic remoteness.** The population of each town at risk of
adoption is estimated using population estimates provided by the Kenya Bureau of Statistics.
KBS provides estimates for approximately 160 towns, while GIS databases classify all towns
according to categorical measures of size. Towns lacking in a KBS population estimate are
assigned the smallest population count of any other town in the database of the same GIS
categorical rating. A town’s at risk population is calculated as the total population minus the
number of previous adopters as well as the share of the town’s population estimated to be in
the low SES group as described above. Geographic remoteness is controlled for by including a
measure of the linear distance from a town to the nearest of Kenya’s six major cities, calculated
using GIS software.

**Construction of town-level characteristics**
The above town-level characteristics are estimated based on district-level data taken from the
three mentioned surveys. Although each survey is conducted at the individual level, two
limitations prevent me from directly estimating town-level attributes and require constructing
town-level estimates from district-level aggregates. The 2005 Kenya Integrated Household
Budget Survey data is only publicly accessible as district-level aggregates. The 2006 and 2009
waves of the FinAccess Survey are available at the individual level, however these surveys lack a
sufficiently large sample size (N=^4,200 in each wave) to create valid town-level estimates.

I use this district-level data to generate town-level estimates by assigning the district
aggregates of each variable to the town, and then estimate population-weighted means for all
towns within a 20-kilometer radius. If a town is more than 20 kilometers from the nearest
district boundary, it will retain its district values. If there are towns in other districts within 20
kilometers, then the town-level measure of each variable will be equal to the mean values
across all towns within the radius, weighted by the number of towns within the radius in each
district. Estimation schemes using radii of 10 and 30 kilometers were calculated but produced
less reliable results.
Methodology
Multilevel negative binomial models are used to estimate the expected number of new investors in each of 563 towns that experience any adoption of the practice in any of six periods, with the first IPO period used to generate lagged profit measures and not directly estimated. The resulting 3,378 observations include 1,326 town-IPO instances where no new investors enter the market; in these cases, profits from that period are coded as 0 for the next period but the observation is not discarded. The multilevel model used generates fixed effects estimates of all independent variables; random town-level effects are controlled for by clustering each model at the town level. All models are estimated using data from all towns, with the exception of Model 8 which performs a robustness check on the influence of alters using a sub-sample of towns with less than 10,000 residents. The full sample of 563 towns represents 98.8% of all towns that contain any adopters of the practice.

The fully specified models addressing research questions 1 and 2, respectively, take the forms:

\[ \text{NewInv}_{it} = \alpha + \Phi IPO_t + \beta_1 TownTraits_{it} + \beta_2 \text{Town}\pi_{it-1} + \beta_3 GeoPeer\pi_{kt-1} + \beta_4 GeoPeer\pi_{kt-1} \times \text{EthnicHomo}_{it} + e_i \]  

(4)

\[ \text{NewInv}_{it} = \alpha + \Phi IPO_t + \beta_1 TownTraits_{it} + \beta_2 \text{Town}\pi_{it-1} + \beta_3 GeoPeer\pi_{kt-1} + \beta_4 GeoPeer\pi_{kt-1} + \beta_5 GeoPeer\pi_{kt-1} + e_i \]  

(5)

\[ i = 1, \ldots, 563 \text{ towns; } j = 1, \ldots, 562 \text{ weighted peers; } t = \text{IPO periods 2 through 7} \]

Where \( IPO_t \) contains dummy variables for each IPO period, whose coefficients are in \( \Phi \) and \( TownTraits_{it} \) is a range of town-level control variables measured during that IPO period. The terms \( \text{Town}\pi_{it-1}, GeoPeer\pi_{kt-1}, \text{ and EthnicPeer}\pi_{kt-1} \) contain measures of profits earned by town residents (equation 2 above) and profits earned by investors in all peer towns weighted by their geographic and ethnic proximity to the focal town (equation 3 above). The term \( GeoPeer\pi_{j} \times \text{EthnicHomo}_{it} \) interacts the level of profits earned in geographically proximate towns with the measure of local ethnic homogeneity. The error term is represented by \( e \).

I model new investor recruitment starting in the second IPO period in order to allow for the profits earned in the first period to be known. Theoretically, this is preferable to allowing profits earned on investments prior to the first IPO to count as the measure of profit, as these investments were much less public in nature and, as seen in Figures 2 through 4 above, a sufficiently small number of individuals participated in the NSE prior to the first IPO that it is untenable to assume that news of profits earned would travel to the same extent.

RESULTS
Descriptive statistics and a correlation matrix for all variables used in the analysis are presented in Table 1. Table 2 shows model estimates that address question #1 while Table 2 shows results addressing question #2. Model 2 in Table 1 form the baseline estimates of town-level
characteristics on the recruitment of new investors; these models are estimated separately to show that town-level populations of each of ten ethno-linguistic groups represents a significant improvement to the fit of the model. A discussion of the significance of particular ethnic groups is beyond the scope of this paper.

**Tables 1 and 2 about here**

In addition to the added explanatory value of individual ethnic groups, Model 2 shows that including measures of ethnic groups changes the effect of town levels of wealth. Towns with a higher proportion of high SES households become a negative indicator of new investor recruitment once ethnic composition is controlled for. Proportion of low SES households serve as the reference group, and Model 2 suggests that high SES towns are significantly less likely to recruit new investors than are medium and low SES towns. This finding is consistent across all models, although in some models medium SES towns are found to be more likely to recruit new investors than low SES towns, although low SES towns remain stronger recruiters than high SES towns. These estimates are consistent with earlier work by organizational sociologists of increasingly risk tolerant behavior by worse performing actors.

Model 3 adds an estimate of town-level profits earned in the previous IPO, showing a positive and highly significant effect of local profits. Model 3, however, falls just short of the threshold for improving model fit over Model 2, suggesting that local, non-networked profits play an unclear role in the recruitment of new investors. I explore this issue further in Models 5 and 6, discussed just below.

Model 4 adds the measure of profit earned in the previous IPO by geographically proximate peers. Measures of profits earned by network peers are estimated in all models according to equation (2) above and using a $v$ of 10. Following Burt (1987), I recognize that values of $v$ are unknowable a priori, and I report estimates based on $v=10$ because they provide the best overall model fit, having also tested values of $v$ ranging from 0.5 to 10. Model estimates of network peer profit are positive and significant at all values of $v$, and values of $v$ smaller than 10 provide estimates of higher magnitude but with weaker model fit. The estimate of geographic peer profits in Model 4 significantly contributes to model fit over Model 3. Based on estimated in Model 4, a one standard deviation in local and geographic peer profits in the previous IPO is expected to yield an increase in the average town’s number of new investors by 6% and 18%, respectively. However, the highly skewed distribution of the local profit measure warrants closer attention.

The measure of local profit is constructed as total profit earned by all investors in a town, hence larger cities, home to a disproportionate number of investors, will take on extreme profit values depending on the performance of the previous IPO. For example, Table 1 shows a maximum value of the local profit measure approximately 40 standard deviations from the mean, reflecting the total profits earned by hundreds of thousands of Nairobi-registered investors in an IPO with a large gain in share price. Models 5 and 6 serve as robustness checks in this regard, with Model 5 estimated using a subsample of only towns with populations less than 10,000
total residents, thus eliminating the influence of the 15% of the observations comprised by the largest cities and towns. Model 6 is estimated using a subsample of only towns where some investor participated in the previous IPO, providing a subsample of observations in which there is complete data for comparing local and peer profits. In both models, the measure of profits earned by geographic peers remains significant and positive. However, the significance of the local profit measure seems to rely on the presence of a critical mass of profits supplied by larger cities, evidenced by the insignificance the local profit measure in Model 5 where large cities are excluded from the analysis. The key finding from these robustness checks is the consistently positive and significant effect of profits earned by geographically proximate peers, a finding that sets up the analysis of local susceptibility to network learning that is the primary focus.

Research question 1 is directly addressed in Model 7, which shows a negative and significant interaction between geographic peer profit and local ethnic homogeneity. This result suggests that localities comprised of higher concentrations of a single ethnic group are less susceptible to influence from outside peers. However, an important counterfactual must be considered. Because the profit measure for each town is expressed as total profits earned by all investors, a plausible alternative to the finding in Model 7 arises if towns located close to the few number of large cities, where profit totals will be higher by definition due to larger numbers of participating investors, are more ethnically heterogeneous. If this is the case, then the result in Model 7 would be true due to proximity to a major city rather than the effect of ethnic homogeneity. Alternatively, it may be the case that the relatively few towns with extreme measures of ethnic homogeneity (the maximum value for ethnic homogeneity is 34, and approximately 8% of the sampled towns have homogeneity scores above 20) drive the negative effect of ethnic homogeneity shown in Model 7. Models 8 and 9 demonstrate the robustness of the finding, however, showing that the result is still obtained even if the 85 observations in the sample representing towns located within 15 kilometers of any major city are excluded (Model 8) or if the 258 observations representing towns with ethnic homogeneity scores above 20 are excluded (Model 9).

The robustness of Model 7 was further explored in a series of models not shown here interacting the homogeneity measure of each of the ten ethno-linguistic groups individually with geographic peer profit. These models show that the interaction effect is not the result of concentrations of particular ethnic groups, as only two of ten ethnic groups have significant interactions. The interaction of local homogeneity of English speakers is positive, while one interaction with a specific ethnic group is negative. However, this group is small enough that it is statistically impossible that it drives the entire effect.

Figure 5 provides a more easily interpretable estimation of the interaction term from Model 7, using the full model to predict the change in the count of new investors in each town at different levels of peer profits and local ethnic homogeneity. Estimates are expressed as ratios of new investors from the previous to the current period, given the values of geographic peer profits and ethnic homogeneity. For example, a perfectly heterogeneous town experiencing the maximum level of peer profit would be expected to double its number of new investors in the next period. A town with an ethnic homogeneity score of 15, however, would recruit very few
additional new investors at this high level of profit. Consistent with the negative coefficient on the interaction term in Model 7, the positive effect of any given level of peer profits is less in more homogeneous towns, suggesting that they are more insulated from the network-based social learning process.

**Figure 5 about here**

Models 7, 8 and 9 show a compelling effect of local ethnic homogeneity on susceptibility to network influence; however, the results are not without some weakness. The robustness checks of the interaction term are significant at the four and five percent levels when I take out towns within 15 kilometers of a major city and any observations more than two standard deviations from the mean of ethnic homogeneity. However, the interaction term becomes insignificant if I move the threshold of distance from a major city out to 20km. I would argue, therefore, that these results support the idea that ethnic homogeneity impedes the transmission of material information through the network, but it’s hard to fully separate this effect from that of being located close to large cities where there exist critical masses of profits capable of sending strong signals to geographically proximate communities. This conjures thoughts of the effect we see about town-level profits, that they’re only significant when we include towns large enough to generate some critical mass of profits. The measure of profit earned by geographic peers also displays some of these qualities, where it’s necessary to be located close enough in the network to a town that generates a critical mass of profits, although local ethnic homogeneity makes each town somewhat less susceptible.

Table 3 directly advances research question 2, and in doing so provides a second method for studying the effects of ethnically diverse society on the network contagion. Model 4 is reproduced in Table 3 to provide a basis for comparison when adding the second network proximity measure based on ethnic distance to that of geographic distance used in the last set of models. Model 10 adds the measure of profits earned by peers in the ethnic network alongside profits earned by geographic peers. Despite the two measures of distance being correlated at almost 0.7, there is enough variation left on the measure of ethnic peer profit to provide a positive coefficient that is significant at the two percent level. Additionally, adding this measure of profit by ethnic peers to a baseline model of profits earned by geographic peers improves model fit significantly. Models 11 and 12 perform the same robustness checks as models 5 and 6, generating estimates using subsamples of only towns less than 10,000 residents (Model 11) and towns with some level of participation in the previous IPO (Model 12). Estimates from Model 11, however, increase the magnitude of the effect of ethnic peers absolutely as well as relative to geographic peers, suggesting that the effects of ethnic network proximity in smaller towns and villages is stronger than in larger towns and cities. The negation of local profit seen in Model 11 is identical to that in Model 5, where local profits fail to be a significant influence on new investor recruitment in small towns that often have no investors in the previous IPO.

**Table 3 about here**
Interpreting the coefficients in Model 11 and 12 suggests that the influence of geographic peers exceeds that of ethnic peers, though both are highly influential. In Model 11, a one standard deviation increase in geographic and ethnic peer profits yield expected changes of 10 and 12 percent, respectively. Interpretations of each variable using Model 12, run on a subsample of towns in which there was participation in the previous IPO, yields expected changes of 16% more new investors given a one standard deviation change in geographic peer profit and a 9% increase in new investors for the same change in ethnic peer profit. These interpretations suggest the relative contributions of geographic versus ethnic networks in carrying material information across different subsamples of Kenyan society.

One final line of analysis is presented in Table 3. Models 13, 14, and 15 provide estimates of network influence using a hybrid measure of distance. Rather than estimating the effects of ethnic and geographic networks individually, I combine them into one measure where ethnic distance is used to inflate geographic distance according to the following:

\[ \text{MixedDist} = \text{GeoDist} + (\text{GeoDist} \times \text{EthnicDist}) \quad (6) \]

Where \text{GeoDist} is calculated using GIS software and \text{EthnicDist} is Lieberson’s measure of qualitative variation, Equation (1) above. Equation (6) has the effect of increasing the measured distance between two proximate towns composed of different ethnic groups while leaving unchanged the distance between neighboring towns with similar ethnic population.

The estimations of the effect of this mixed distance measure are directly comparable to those in models 4, 5, and 6. Run on a sample of all towns, the expected change in the number of new investors in a town given a one standard deviation change in geographic and mixed peer profit measures is 18 and 17%, respectively. Run on a subsample of only smaller towns, the mixed peer profit measure (Model 14) becomes more influential, predicting 14% more new investors given a one standard deviation change in network profits compared to a 12% change for only geographic profits (Model 5). The influence of geographic profit remains smaller even when run on a comparable sample of towns with investors in the previous IPO, with geographic profits predicting an 18% increase in new investors from a one standard deviation change and the mixed measure predicting a 20% change. The pattern in comparing these two measures is somewhat like the comparison of the effects of ethnic and geographic distance in models 10, 11, and 12, with geographic distance being the more influential measure for all towns in the sample. However, in all forms of the comparison, restricting the sample to smaller towns and villages less than 10,000 residents suggests a larger causal role for ethnic networks.

**DISCUSSION AND CONCLUSION**

The analysis presented here deepens our understanding of the global effort to institutionalize neoliberal market structures by developing and applying theories of network diffusion to the study of new investor recruitment in the challenging environment of Kenya. The paper also provided a rare opportunity to study the relative contribution of two different network structures in the spread of material information, as well as providing the first empirical measurement of the ethnic networks that link communities in a developing country. Two major findings result from the analysis. First, high levels of ethnic homogeneity in a community
mitigate the network contagion of material information about profits earned by geographically proximate previous investors on potential investors, resulting in fewer new investors recruited from homogeneous towns following highly profitable IPO events. Second, ethnic networks linking towns with similar tribal populations serve as strong pathways for the spread of material information about earlier profits earned by co-ethnics, contributing significantly to the recruitment of new investors even after the effects of geographic proximity are controlled for. The evidence presented here on the role of social networks in recruiting new investors overwhelmingly supports the conclusion that the experiences of prior entrants into the Kenyan stock exchange influence residents in proximate towns to purchase shares in later periods, even after extensive efforts are made to control for intrinsic characteristics of investors (wealth, financial literacy, geographic remoteness, numbers of previous adopters, informal norms of specific ethnic groups, exposure to IPO advertising campaigns) as well as characteristics of listing firms and conditions in the national environment at the time of each IPO event.

The results presented here have the potential to significantly contribute to policy makers’ efforts to generate functional capital markets in challenging environments. Economists discuss both the benefits associated with a functional stock market in a developing country (e.g. Levine 1996; Levine and Zervos 1998) as well as question their appropriateness as a financial technology in the developing world (e.g. Kenny & Moss 1998; Singh 1999; Stiglitz 1989), but often overlook how a stock exchange reaches some level of maturity. Policy makers either implicitly or explicitly assume that investors will populate a stock exchange once created, conditional on a sufficiently established nexus of supporting institutional elements, especially legal institutions (La Porta, Lopez-de-Silanes, & Shleifer 1997). Several endogenous processes of financial market growth have been proposed, including firm-centric accounts of seeking private capital when bank lending becomes too costly (Greenwood & Smith 1997) and investor-centric explanations that some minimum level of liquidity in a stock exchange incrementally attracts additional investors in an escalating and self-reinforcing manner (Levine 1991; Bencivenga, Smith, & Starr 1995; Rousseau & Wachtel 2000). These studies, however, leave unanswered the question of how stock exchanges initially attract investors that serve as seeds in this endogenous process as well as the individual-level mechanisms that perpetuate further expansion once begun. Given that most emerging stock exchanges are located in weak institutional arrangements expected to make potential investors reticent to participate, the question of how investors are recruited into the practice is especially pressing. This paper presents perhaps the first quantitative study of the recruitment of new investors, accounting for the contributions of structural characteristics of investors and firms as well as two types of social networks and the susceptibility of local communities to network influence.

The results presented here show no signs of a mimetic process whereby sheer numbers of previous adopters influence later adoption as the practice becomes increasingly taken for granted (Tolbert & Zucker 1983; see also Rossman 2010); however, investigating attributes of early investors within the town, especially wealthier investors with larger portfolio values, may provide qualitative evidence of the process suggested by Preda(2001; 2005) who makes the qualitative argument that participation in the English and French financial markets in the 1800s increased as it was legitimated by an expanding “knowledge frame,” facilitated by the increased
prevalence of investor manuals and other materials that increased cognitive understanding of
the practice as well as the increasing social status of those that participated in market.
Attending to local-level social interactions between current and potential investors is also
suggested by several studies by economists, who find that stock market participation in the U.S.
is positively influenced by measures of social interaction in religious and civic organizations
(Hong, Kubik & Stein (2004) and that participation in employer-sponsored retirement plans is
positively influenced by workplace peer participation (Dufle & Saez 2002). Future research in
this area might seek to expand on the local-level diffusion of shareholding in Kenya through
further data collection showing individual attributes of investors, attending to status
characteristics and other symbolic measures in addition to the financial value of investments. It
is entirely possible that local diffusion of the process depends on the number and status of
previous adopters, as suggested by Preda; however, this is not the central question of concern
in this paper.

To mitigate concerns about generalizability, I suggest that the nature of ethnic cleavages seen
in Kenya do not differ qualitatively or quantitatively from cleavages observed in other countries
in both the developed and developing worlds. The evidence presented here from Kenya closely
matches previous studies of urban areas in developed countries. City-level studies conducted in
the U.S. suggest that increased ethnic fractionalization results in lower public goods provision
such as schools and roads (Alesina, Baqir & Easterly 2000), where fractionalization can occur
along racial lines between groups from the same country of origin. A large literature that
follows from Tiebout’s (1956) seminal work shows that high socio-economic status groups work
to spatially isolate themselves from lower SES groups in order to avoid redistributive tax
policies. Taken together, these literatures suggest that the same process of insulation from
social learning by fractionalized groups takes place in developed economies as well, similarly
hindering the formation of market structures.

The dataset employed here might be strengthened even further by accessing the individual-
level survey data from the 2005 Kenya Integrated Household Budget Survey (N=13,450), which
includes enough respondents to reliably estimate the town-level characteristics used here
without relying on secondary estimated based on district averages. Access to this individual
survey data would generate more precise town-level estimates, however, it is unclear that the
overall quality of the estimates would improve significantly or that the results of the analysis
would change.

The development of functional market institutions in challenging environments is a challenge to
be met in scores of countries around the world. Beyond improving data collection in Kenya, it is
hoped that the empirical and theoretical effort presented here inspires others to seek out data
collection opportunities in novel locations and in doing so recognize that developing economies
represent fertile natural laboratories for revising and extending theories of economic action
that are directly applicable in developed countries as well.

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Yenkey, C. Forthcoming. Selling Value in Kenya’s Nairobi Stock Exchange. In The Worth of
Figure 1: Total Investor Accounts Over Time
Figure 2: New Investor Account Creation, daily

![New Investor Account Creation, daily](image)

Figure 3: Geographic distribution of Kenyan shareholders, early and all adopters

Dec 2005: 444 towns; 135,000 investors  Dec 2008: 575 towns; 1.4 million investors

![Geographic distribution of Kenyan shareholders](image)
Figure 4: Share Price Performance of Each IPO at the Start of the Next IPO

Figure 5: Estimated Change in New Investor Recruitment at Given Levels of Peer Profit (t-1) and Ethnic Homogeneity
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 No. new investors</td>
<td>198</td>
<td>3,822</td>
<td>0</td>
<td>205,614</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 Town profit (Tens mill. Ksh)</td>
<td>0.15</td>
<td>19.63</td>
<td>-783</td>
<td>814</td>
<td>0.172</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Geographic peer profit (Tens mill. Ksh)</td>
<td>1.65</td>
<td>16.50</td>
<td>-77.83</td>
<td>88.47</td>
<td>0.001</td>
<td>0.024</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 Ethnic peer profit (Tens mill. Ksh)</td>
<td>0.08</td>
<td>0.48</td>
<td>-2.30</td>
<td>3.09</td>
<td>0.001</td>
<td>0.063</td>
<td>0.696</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 Hybrid profit (geography and ethnicity; Millions Ksh)</td>
<td>0.16</td>
<td>1.58</td>
<td>-6.87</td>
<td>7.87</td>
<td>0.001</td>
<td>0.025</td>
<td>0.997</td>
<td>0.724</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6 No. of investors in previous IPO (000's)</td>
<td>0.39</td>
<td>6.43</td>
<td>0</td>
<td>313</td>
<td>0.325</td>
<td>-0.018</td>
<td>-0.045</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7 Distance of town to nearest major city (km)</td>
<td>69.26</td>
<td>66.58</td>
<td>0</td>
<td>637</td>
<td>-0.037</td>
<td>-0.005</td>
<td>-0.019</td>
<td>-0.009</td>
<td>-0.018</td>
<td>-0.045</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8 Town's at risk population (000's)</td>
<td>5.76</td>
<td>75.19</td>
<td>0</td>
<td>1,864</td>
<td>0.586</td>
<td>0.057</td>
<td>-0.001</td>
<td>0.001</td>
<td>-0.004</td>
<td>-0.784</td>
<td>-0.064</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9 SES high (%)</td>
<td>4.49</td>
<td>1.08</td>
<td>0</td>
<td>54.96</td>
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### Table 1

Descriptive Statistics and Correlation Matrix of all Variables in the Analysis (N=3,378)

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<th>Swahili (%)</th>
<th>Kikuyu (%)</th>
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### Notes
- All variables are standardized.
- The correlation matrix shows the Pearson correlation coefficients between variables.
### Table 2

**Negative Binomial Estimates of Count of New Investors in Each Town in Each IPO**

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* p<.05  ** p<.02  *** p<.001

Robust standard errors are in parentheses

**Note:** Estimates of IPO period dummies not displayed
### Table 3

**Negative Binomial Estimates of New Investors in Each Town in Each IPO**

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**Predictive variable**

| Town profit                      | .003*** | .003*** | .092    | .002**  | .003*** | .098    | .002*** |
|                                  | (.001)  | (.001)  | (.074)  | (.001)  | (.001)  | (.074)  | (.001)  |
| Geographic peer profit           | .010*** | .009*** | .006**  | .009*** | .006**  | .009*** | .006**  |
|                                  | (.002)  | (.002)  | (.002)  | (.002)  | (.002)  | (.002)  | (.002)  |
| Ethnic peer profit               | .197**  | .234**  | .186*   | .083    | .097    | .083    | .083    |
|                                  | (.032)  | (.032)  | (.032)  | (.032)  | (.032)  | (.032)  | (.032)  |
| Hybrid profit (geography and ethnicity) | .107**  | .082**  | .113**  | .018    | .025    | .018    | .018    |
|                                  | (.382)  | (.385)  | (.390)  | (.382)  | (.492)  | (.388)  | (.388)  |

**Constant**

| Constant                         | -1.41***| -1.45***| -1.37***| -1.29***| -1.42***| -1.35** | -1.27** |
|                                  | (.382)  | (.385)  | (.495)  | (.390)  | (.382)  | (.492)  | (.388)  |
| Chi-squared                      | 25205   | 25284   | 18494   | 23177   | 25181   | 18378   | 23051   |
| Deg. of Freedom                  | 24      | 25      | 25      | 25      | 24      | 24      | 24      |
| No. obs                          | 3372    | 3372    | 2850    | 2428    | 3372    | 2850    | 2428    |

* p<.05  ** p<.02  *** p<.001

Robust standard errors are in parentheses

Note: Estimates of IPO period dummies not displayed