Competition, social learning, and technology adoption: The case of mobile money in Peruvian markets

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Abstract*

Technology adoption by small and microenterprises is poorly understood although their low productivity is a well-known obstacle to economic development. A unique empirical setting, the spread of electronic wallets (mobile money) among vendors in popular markets in Peru, allows us to identify the respective contributions of two key determinants of technology adoption by these firms: competitive pressures and social learning. Using self-collected panel data on vendor behavior in three markets, we estimate the effect on the probability of mobile money adoption of prior adoption by: vendors who are competitors, who are members of a vendor's social network, or by vendors who are neither competitors nor network members. The literature emphasizes the importance of social learning. Nevertheless, adoption by competing vendors has a larger and more robust effect on own-adoption than adoption by members of a vendor's social network. The effect persists in multiple robustness tests, including controls for the proximity of vendors. These conclusions suggest that public policy that to encourage technology take-up by small, low-productivity firms could usefully place greater emphasis on competition to complement the existing focus on extension-type services.

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Introduction

The literature has long debated the effect of competition on innovation and struggled to disentangle the impact of competitive pressures from confounding factors. A unique empirical setting allows us to distinguish the effects of competition from one confounding factor, social learning. On the one hand, the experience of early adopters in a firm's own industry provides information, through "social learning", about the risks entailed by adopting the new technology. On the other hand, early adoption by other firms in the industry poses a competitive threat to non-adopters. The adoption of electronic wallets or mobile money by vendors in food markets in Peru allows us to distinguish these two effects. We find that early adoption by other vendors who share the same market and production function, but sell different products, significantly increases vendor own-adoption. However, prior adoption by competitors – other vendors who sell the same products – increases own-adoption even more.

Mobile money is a smartphone application that allows users to receive and transfer money from their devices. The adoption of this technology was rapid in some areas, like the capital city, Lima; but slower in others, particularly those where financial and digital inclusion were already low. This pattern reflects the more general obstacles to the spread of innovation. Firms must exert effort to discover new technology, to assess its value to the firm, and to acquire and integrate it into firm operations. Although adopting mobile money in Peru does not imply any monetary investment, it does demand that vendors learn how to use the mobile money application.[1] Adoption is also risky, exposing vendors to scams. Learning is therefore particularly important since ill-informed usage exposes vendors to greater risk.

We study the role of competition and social learning in mobile money adoption by urban vendors in traditional markets. Vendors compete against other vendors in the same product category to attract customers and increase their earnings. On the other hand, traditional market vendors often share family and friendship links, which enhances social learning. In this paper, we compare the role of these two determinants in digital technology adoption by market vendors in an urban setting, in contrast with most prior research that focuses on agricultural technology adoption in rural settings.

In Peru, commercial banks created their own mobile money applications and periodically launched campaigns in popular markets to encourage adoption. We conducted a census in three popular food markets before they were targeted with such as campaign. The census yielded information on vendor characteristics, including product lines; family and friend social networks inside the market; and mobile money adoption. We then visited the markets twice more, one and two months after the campaign, to track changes in mobile money adoption by the vendors. Using the social network data and timing of adoption, we estimate the independent effects of social learning and competition on mobile money adoption.

We find strong evidence that, in contexts where both competition and social learning are present, competition incentives are stronger. However, these effects may be even stronger when relatives/friends who adopted before are also competitors. While competition is the main driver of technology adoption, social learning can also play a role when individuals not only trust their peers, but also know they have valid information about their context.

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[1] In our data, 78% of vendors have a Smartphone with internet access.

Our findings concerning the importance of competition relative to social learning have significant policy implications. First, they contribute to better understanding about the factors that trigger adoption of a particularly important technology, mobile money (or "electronic wallets"). The technology has provoked significant interest in part for its potential to increase financial inclusion. Only half of Peruvian adults have a bank account, and even fewer in low socioeconomic districts located in the outskirts of cities (National Households Survey 2022). Second, to the extent that social learning matters most for technology adoption, public policies should aim at disseminating credible information to firms. However, to the extent that competition drives technology adoption, public policy should focus instead on removing barriers to entry that limit competition.

The analysis contributes to large bodies of research on technology adoption and, specifically, mobile money; these contributions are described in the next section. We then discuss the spread of electronic wallets in Peru and the details of our data collection effort. We then report a number of analyses of these data, demonstrating in multiple specifications the robust influence of competitive pressures on technology adoption by microenterprises.

Literature Review

Social learning, the observation of successful adoption by peers, informs potential adopters of the existence of the technology, its likely value, and the feasibility of adoption. Firms' ability to make inferences from the experience of other firms depends, though, on how similar those firms are. Competitors are most similar, but greater competition also threatens firms with lower profits unless they exert effort to adopt new technology. Prior research has focused on the effects of either competition or social learning on the adoption of new technologies, but with few exceptions, not both simultaneously.[2]

A significant body of work examines the effects of competition and, especially, social learning on technology adoption. Like we do, Machokoto, Gyimah, and Ntim (2021) examine social learning and competition in a sample of 4,500 US firms. They find greater spending on corporate R&D among peers prompts more own-innovation by firms; these effects are increasing in product market competition. De Mel, MacKenzie, and Woodruff (2009) analyze data from a survey of a large sample of Sri Lankan firms and conclude that larger firms are more likely to report innovative activity, but firms reporting more competitors in their area are no more innovative than those reporting fewer. We complement these efforts by analyzing data from a sample of highly firms that are almost identical on observables and, therefore, plausibly similar on unobservable characteristics that might influence technology adoption. Further, we can precisely observe competition, social learning, and the adoption of a specific, salient technological innovation.

Other research on competition and innovation has a different focus than the one here. It examines whether, consistent with Aghion et al., competition prompts firms that are at the technological frontier to innovate more to maintain their lead, while discouraging firms from innovating that are further from the frontier. Macher, et al. (2021) find that competition reduces the probability of adopting a cost-reducing technology in the cement industry (the precalciner kiln), a result they attribute to the limitations that nearby competitors impose on plant scale, reducing the potential savings from adopting the kiln. Cusolito, García-Marin, and Mahoney (2023) examine the effects of the competitive shock of Chinese imports on innovation in Chilean manufacturing plants and conclude that it

[2] Ilzetzki (2023) identifies a third motivation to innovate, capacity constraints. Increased government purchases of World War II aircraft in the United States prompted significant managerial and productive innovation, but only at the most capacity-constrained plants.

influences innovation in the most productive plants, but depresses it in the remainder. Zuñiga Lara and Benavente (2022), in contrast, find a linear, positive effect of (within-country) competition on innovation in Chile, but find that innovation rises and then falls with competition in Colombia. Helpman (2023) develops a model showing that import competition can increase or decrease investment in innovation by large, domestic multiproduct firms depending on their productivity. Milliou and Petrakis (2011) model technology adoption under Cournot and Bertran competition and find that the first can lead to earlier adoption than the second, and that greater competition does not always encourage adoption.

Research on innovation and social learning goes back decades. Most of it has focused on the adoption of agricultural technologies (seeds, fertilizers, planting techniques) by poor farmers. Most recent contributions find that famers are more likely to adopt innovations when they observe local peers who have adopted them and experienced exceptional outcomes (Bandiera and Rasul 2006, Conley and Udry 2010, and Nakano et al. 2018). Consistent with the proposed mechanism, Bandiera and Rasul (2006) find that individuals with more information about the new technology, who have less to learn from peer adoption, are correspondingly less influenced by their peers' adoption. An individual can learn about a new technology just by mimicking another individual (Banerjee, 1992; Agranov et al., 2022). However, family and friendship bonds should facilitate information sharing and, consistent with this, in Bandiera and Rasul (2006), adoption is more correlated among family and friends. Similarly, Nakano et al. (2018) find that relatives or neighbors of farmers who have received agricultural training are more likely to adopt new technologies compared to those who are not relatives or neighbors.

Several studies have compared the role of social learning in the adoption of agricultural technology with traditional methods, such as extension services. Krishnan and Patnam (2014) found that after social learning is what drives the expansion of technology and its benefits, following an initial push from extension services. As we do, they argue that having common characteristics is positively correlated with social learning. Similarly, Takahashi et al. (2019) conducted an experiment where treated units were provided extension services and were asked not to exchange information with control units, which were also discouraged to ask treated units for information. Differences between the treatment and control arms disappeared when the communication restriction was lifted. Alidaee (2023) argues that information from peers is valuable because, on the one hand, the returns to technology adoption can vary depending on individual or firm characteristics but, on the other hand, individuals have more information about the characteristics of their peers, allowing them to control for this variation.

Our study complements this work by expanding beyond agricultural technology and by considering the role of competition.[3] Fear of losing market share can generally not account for the results in research on farmer behavior since the farmers in these studies are price-takers: increased production by peer farmers who adopt new technologies does not affect the prices faced by peer farmers who do not (Conley and Udry 2010).[4]

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[3] Most research on social learning in technology adoption is focused on agricultural technology (Foster and Rosenzweig, 2010; Maertens and Barret, 2012). Notable exceptions include Goolsbee and Klenow (2002), who examine the timing of first-time purchases of home computers, and Oster and Thornton (2012), who study the early adoption of menstrual cups in urban Nepal schools.

[4] However, in a laboratory experiment, Vasilaky and Islam (2018) find that information sharing is greater when subjects confront tournament-style, more competitive incentives than team-based, more cooperative incentives.

Finally, our study is relevant to a growing literature on mobile money. Aker et al. (2016), Jack y Suri (2014), Suri y Jack (2016), Suri (2017), Riley (2018) and Lee et al. (2021) have documented positive impacts on income, savings, consumption, food security, and money transfers to help relatives. Agarwal et al. (2019) examine the impact on mobile money among small merchants in Singapore and find that adopters attract more new customers who pay by mobile money. In a different study of mobile money adoption among microentrepreneurs in Malawi, Aggarwal et al. (2020) find the largest effects on saving behavior rather than on transactions. Bian, et al. (2023) conclude that e-wallet transactions facilitates the use of buy-now-pay-later consumer credit schemes and substantially expand access to credit among underserved consumers.

Given these positive effects, the factors that determine mobile money adoption are relevant. Our contribution examines two determinants of adoption, social learning and competition, not considered in prior work. Jack and Suri (2011) and Aker and Mbiti (2010) point to age, gender and education level. Batista and Vicente (2020) find that early adopters are more educated and are more likely to have bank accounts, to be employed and to be wage earners.

In sum, we contribute to the literature in three ways. First, we analyze the comparative role of competition and social learning in technology adoption. Most studies do not consider competition as its incentives are absent in their context, but these interactions can also have a substantial effect. Second, we study determinants of technology adoption in an urban context. While most studies are focused in agricultural technology, technology adoption in urban environments is crucial, given the marked urbanization patterns in developing countries. Third, we contribute to the literature on mobile money by studying the role of social learning and competition. As Suri (2017) concludes, these supply-side factors are key to understanding patterns of mobile money adoption.

Data

The data were collected from vendors in popular markets in the poorer areas of Chiclayo, a provincial city in Peru. They sell to a common set of consumers using nearly identical production processes. Given the commonality of their production processes and customer bases, and their mutual observability, all vendors in a market constitute peers whose adoption of new technology offers opportunities for social learning. However, vendors differ in whether they compete with each other: those who sell different products are simply peers, but those who sell the same products are both peers and competitors. The use of mobile money allows vendors to differentiate themselves from otherwise essentially identical competitors. In this setting with highly homogeneous peers, use by any vendor offers information about the value of technology. Hence, if adoption by peers who sell the same products is more likely to trigger adoption than adoption by non-competing peers, we can infer that fear of losing market share is a significant driver of technology adoption.

The Peruvian Banks Association (ASBANC) and leading commercial banks launched a campaign in 2021 to promote mobile money among traditional market vendors.[5] Traditional markets were targeted because nearly 90% of Peruvian urban households regularly shop there, especially in low-income neighborhoods. The campaign

[5] Such a promotion campaign is well-grounded theoretically. As Crouzet, et al. (2023) find, coordination frictions can hinder technology adoption. Focusing on electronic wallets, they conclude that shocks that overcome these frictions (in their case, a large exogenous contraction in the supply of cash in India) can dramatically increase adoption.

started in the capital city of Lima and rapidly expanded to other major cities. We focused on Chiclayo, the fourth largest city in Peru, because mobile money adoption was still modest, particularly in the outskirts of the city.

We collected three rounds of census data in three traditional markets located in the outskirts of Chiclayo. The first round of data was collected in March 2022, before the ASBANC campaign to promote mobile money in these markets. Data included vendor characteristics, family and friend social networks inside the market, and mobile money adoption. The second and third rounds were collected 20 and 50 days after, respectively; their objective was to monitor mobile money adoption by vendors and collect data on the effectiveness of the campaign. Short periods between rounds were chosen to be able to capture changes in adoption in case they were rapid, which could be the case according to qualitative evidence we had collected.

We collected data on 293 vendors. *Table 1* shows some characteristics of the three markets. They vary in size, both in terms of number of vendors and area. Market 3 is the biggest, and also exhibits better quality walls, floors and ceiling. In contrast, Market 1 is the smallest market, but also the newest and the only one that is privately owned, rather than cooperatively governed by all the vendors. In all markets, vendors who sell groceries are most numerous. However, large numbers sell chicken, fruit, and vegetables. Some sell clothing, serve prepared food, or sell household items.

Table 1. Characteristics by market

Characteristics	Market 1	Market 2	Market 3
# vendors	58	87	148
Area (m2)	400	1248	2420
Year of foundation	2016	1980	1991
Property	Private	Public	Public
Materials index (1-3)*	1.5	1.5	2.5
Vendors distribution by category			
% groceries	22.4	29.9	29.7
% chicken	12.1	8.1	8.1
% vegetables	13.8	11.5	9.5
% clothing	3.5	4.6	12.2
% menu	10.3	10.3	5.4
% bazaar	10.3	5.8	6.8
% meat	3.5	6.9	4.1
% fruit	5.2	6.9	2.7
% juice	1.7	3.5	4.7
% sea food	3.5	6.9	1.4

*This index is based on the materials quality of walls, floor, and ceiling of the market. The higher the index, the better the quality.

There are also key differences among markets regarding its merchants' characteristics. As Table 2 shows, vendors from Market 1 are younger, better educated, and better digitally and financially included. On the contrary, vendors from Market 3 are older, less educated and included, both digital and financially. Market 2 is an intermediate position between the other two.

Table 2. Merchant characteristics by market

Characteristics	Market 1	Market 2	Market 3	Total
% women	0.69	0.77	0.76	0.75
Age	38.2	51.7	47.8	47.1
Less than complete high school	0.12	0.29	0.37	0.30
# weekly clients (log)	5.16	5.20	4.68	4.92
Has smartphone with internet access	1.00	0.81	0.69	0.78
Lives with someone between 15-50 years	0.98	0.73	0.86	0.85
Uses at least one financial service*	0.73	0.42	0.38	0.45
Lottery S/ 1,000 (log)**	1.72	2.06	2.07	2.01
Double size stand	0.38	0.20	0.25	0.26
Has assistant between 15-50 years	0.27	0.18	0.27	0.24

*Financial services considered are: having debit or credit card, uses ATM, uses bank application

**This variable is based on the question: "Imagine that there is a S/ 1,000 lottery and there are only five tickets. What is the maximum amount of money that you would be willing to pay in order to participate in the lottery?" (S/ 1,000 is approximately 250 $)

A crucial matter in this study is the differences in the timing of adoption among vendors. However, according to qualitative evidence we collected previously, it could be difficult for vendors to recall the exact date when they adopted mobile money. Thus, in the first round we asked each vendor who had already adopted mobile money about their estimated date of adoption using periods, i.e. less than two weeks ago, between two weeks and one month, and so on. *Table 2* presents the adoption rate for each market by period. There are some facts to consider. First, 40 vendors adopted mobile money more than a year ago. This implies those vendors adopted mobile money early in 2021, which coincides with the start of its promotion in traditional markets. Second, 40 vendors adopted mobile money after the ASBANC campaign (between rounds 1 and 3). This suggests the ASBANC campaign was not very effective in these markets. Furthermore, in the third round only 56% of vendors reported to have chat with ASBANC promoters to adopt mobile money. Third, the adoption rate varies considerably by market, with Market 1 having the highest rates.

Table 3. Mobile money adoption rate by market

Period	Market 1 # by period	Market 1 % cum	Market 2 # by period	Market 2 % cum	Market 3 # by period	Market 3 % cum	Total
More than 1 year ago	23	40%	9	10%	8	5%	40
6 months to 1 year	10	57%	6	17%	5	9%	21
1 month to 6 months	7	69%	7	25%	9	15%	23
2 weeks to 1 month	1	71%	3	29%	2	16%	6
Less than 2 weeks	1	72%	0	29%	1	17%	2
Between R1 and R2	7	84%	11	41%	7	22%	25
Between R2 and R3	2	88%	6	48%	7	26%	15
Total adopters	51		42		39		132
Non adopters	7		45		109		161

We use the periods described in Table 2 to build a seven-period panel. In addition, we exploit the timing of adoption of merchants to construct key competition and social learning variables. The competition variable is the share of its competitors that adopted mobile money until that period. We know vendor categories and when they adopted electronic wallets. Hence, we know when the competitors of each vendor adopted electronic wallets. Qualitative evidence collected during the field visits confirms that at least some vendors recognized that not accepting mobile money put them at a disadvantage. They understood that if a customer asked to pay with an electronic wallet and the vendor did not accept it, the vendor would lose the sale to a competitor who did accept mobile money.

Regarding social learning variables, in the first round we asked each vendor if they had: (i) relatives in the market, and (ii) friends, indicating specifically "people whom they trusted", in the market. For each group (family and friends), we asked them to list a maximum of five individuals. Thus, we were able to build the social networks within each market. As we conducted censuses in each market, we were able to link each vendor's relatives/friends from the market with the timing of mobile money adoption. Hence, we could calculate, for each vendor, the share of their relatives/friends who had already adopted mobile money at each period.[6]

The competition and social learning variables tend to overlap. The physical organization of markets commonly locates vendors from the same category close together. It is also likely that vendors' friends have contiguous stands, so competitors may also be relatives or friends. For this reason, we employ four variables that comprise all the possible overlaps between these variables.

"Non-social non-competitors" is the share of all those vendors in the market who are not relatives/friends nor competitors of the vendor and who adopted mobile money. This variable is highly correlated with the overall rate of adoption in the market.

"Social competitors" is the share of all those vendors in the market relatives/friends who are also competitors and who adopted mobile money. "Non-social

[6] We use this approximation because some of the periods are lengthy, for instance, '6 months to 1 year'.

competitors" is the share of competitors who are not relatives or friends of the merchant who adopted mobile money. "Social non-competitors" is the share of relatives/friends who are not competitors of the merchant who adopted mobile money.

Table 3 shows the evolution of these variables through time. While all the shares increase with time, as we would expect, the groups that vary the most are the non-social non-competitors and non-social competitors.

Table 4. Competition and social variables by period

	Share of market vendors who have adopted mobile money and are:			
Period	Non-social non-competitors	Social competitors	Non-social competitors	Social non-competitors
1	0.14	0.02	0.12	0.03
2	0.20	0.05	0.20	0.08
3	0.28	0.06	0.27	0.09
4	0.31	0.07	0.29	0.13
5	0.31	0.08	0.30	0.13
6	0.40	0.09	0.39	0.15
7	0.45	0.09	0.44	0.16

Estimation strategy

The main specification we use to estimate the effects of social learning and competition on technology adoption is given by equation (1):

$$(1)\quad Adoption_{imt} = \beta_0 + \beta_1 SL - Comp_{imt} + \tau_t + \alpha_i + \varepsilon_{imt}$$

The dependent variable $Adoption_{imt}$ is a dummy variable that denotes whether vendor i from market m was using mobile money in period t. $SL - Comp_{imt}$ are the competition and social learning variables. τ_t and α_i are period and merchant dummies. Finally, ε_{im} is the error term. We control for vendor fixed effects so we cannot include other time-invariant control variables, such as market and category dummies or vendor characteristics. Finally, because our main variables are shares with different denominators, we normalized them to make the coefficients comparable.

Our focus on equation (1) follows the literature in estimating correlations among technology adoption, competition, and social learning. However, three features of our data allow us to make stronger causal inferences from competition and social learning to technology adoption. First, our variables are narrowly defined, restricting the potential for spurious correlations with unobserved vendor characteristics. We examine one specific type of social learning, limiting our analysis to relatives and friends; we consider one specific innovation; and we precisely identify competitors. Second, as in the research that examines farmer adoption of agricultural innovation, vendors are exceptionally homogeneous on observables. Third, given that we know the adoption period, we know which vendor adopted before/after their relatives/friends, exactly consistent with the possibility of social learning. Fourth, we control for vendor fixed effects, excluding any role for unobserved market characteristics and requiring that omitted variables can only exert a spurious influence on these correlations if they co-vary over time in the same way as the pattern of adoption. Finally, we collected census data on each market and are able to control for detailed vendors characteristics.

It could be the case that mobile money adoption influences social networks. Nonetheless, our social network data was collected before most of vendors adopted mobile money. In addition, we focus on family and friendship bonds. The first ones do not change over time, and when asking for friendship bonds, we specifically asked vendors for people they trusted. Hence, both types of bonds should not vary over short periods of time, ruling out the possibility of mobile money adoption affecting social networks.

Results

Table 5 presents the results of estimating equation (1), focusing on the broad competition and social learning variables. All specifications include period dummies and vendor fixed effects. Column (1) estimates whether the share of all vendors in the market who have adopted mobile money by time *t* is correlated with the probability of adoption in time *t*. The coefficient is positive and statistically significant.

The column (2) specification adds a competition variable: the share of competitors who adopted until that period. Both coefficients are positive and statistically significant. Since they overlap – competitors are also accounted for in the market – the competition coefficient is the additional effect of competitor adoption, beyond the effect of general diffusion in the market. That additional effect is large and significant. In column (3) we add the aggregate social variable: the share of relatives/friends who have adopted mobile money, which also overlaps with the other two variables. The competition variable remains statistically significant and largely unchanged.

The column (4) specification disaggregates the four categories of vendors: non-social, non-competitors; social non-competitors; non-social competitors; and social competitors. These comprise all the combination between competition and social learning, avoiding overlapping variables. All the coefficients are positive and all but one are significant. Only the adoption by social non-competitors is statistically insignificant.

The estimated effect of adoption by non-social non-competitor vendors captures a pure imitation effect, unmediated by economic or social factors. The effect of adoption by social competitors combines the effects of competition and social learning; its coefficient is, not surprisingly, positive, and statistically significant. However, the coefficient is not larger than the estimated effect of non-social competitors. In contrast, adoption by social non-competitors is insignificant. We interpret these results to mean that competitive pressures are crucial to the decision of vendors in the market to adopt mobile money.

Table 5. Factors influencing mobile money adoption

	(1)	(2)	(3)	(4)
VARIABLES	Base	Competition	Competition and Social	No overlap
Market	0.159***	0.103*	0.0992	
	(0.0519)	(0.0599)	(0.0602)	
Competition		0.0674**	0.0646*	
		(0.0328)	(0.0329)	
Social			0.0183	
			(0.0186)	
Non-social non-competitors				0.201***
				(0.0552)
Social competitors				0.0494**
				(0.0243)
Non-social competitors				0.0526*
				(0.0302)
Social non-competitors				0.00220
				(0.0158)
Constant	0.240***	0.238***	0.239***	0.308***
	(0.0390)	(0.0388)	(0.0385)	(0.0363)
Observations	1,974	1,974	1,974	1,974
R-squared	0.190	0.200	0.201	0.221
Merchants	282	282	282	282
Model	FE	FE	FE	FE
Period dummies	YES	YES	YES	YES

Eleven merchants were excluded from the analysis because we lacked their information in key variables

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Robustness

Additional analyses point to the robustness of the results discussed above. Table 6 includes four additional specifications for the FE panel model. First, it is possible that early or first adopters in fact have unobserved characteristics that make could spuriously drive the correlations we observe. Hence, in column (1) we discard the merchants who adopted mobile money more than one year before (the early adopters). Column 1 estimates are little changed from those in Table 5.

The organization of Market 1 is notably different from the others'. It is smaller, newer, has younger and better educated merchants, and its adoption rate is higher. These differences may influence the rate of adoption of mobile money. In column (2), therefore, we exclude all of the vendors from this market. Again, the results are little changed.

The analyses have ignored the spatial distribution of adopters and non-adopters. It could be that it is spatial proximity rather than competition or social connections that drives our results. Since some nearby vendors are neither competitors nor socially connected, and some distant vendors are competitors or connected, we can identify the separate effect of proximity on adoption. We created a map that shows the distribution of vendor stands within the markets. Exploiting this and timing of adoption we created a spatial variable to control for the possibility that vendors adopt mobile money because of neighbor adoption.

We define 'close stands' as those that are directly in the sightline of a vendor. Normally, a vendor has five of these stands (one at their left side, three in front and another at their right), however, this can vary depending on the spatial distribution of stands. In column (3) we include this variable. Neighbor adoption is not significantly correlated with own-adoption; its inclusion has little effect on the other estimates.

Table 6. Additional panel specifications

	(1)	(2)	(3)	(4)
VARIABLES	No early adopters	Without Market 1	Spatial variables	Lagged variables
Non-social non-competitors	0.276***	0.161**	0.209***	0.209***
	(0.0792)	(0.0769)	(0.0551)	(0.0614)
Social competitors	0.0403	0.0559*	0.0515**	0.0439
	(0.0370)	(0.0293)	(0.0245)	(0.0308)
Non-social competitors	0.0907***	0.102***	0.0550*	0.0534**
	(0.0348)	(0.0348)	(0.0301)	(0.0247)
Social non-competitors	-0.0155	-0.00994	0.00273	-0.00902
	(0.0173)	(0.0148)	(0.0158)	(0.0166)
Close stands			-0.0521	
			(0.0673)	
Constant	0.262***	0.316***	0.322***	0.287***
	(0.0411)	(0.0753)	(0.0400)	(0.0466)
Observations	1,482	1,610	1,974	1,482
R-squared	0.210	0.207	0.222	0.199
Merchants	247	230	282	247
Model	FE	FE	FE	FE
Period dummies	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Instead of asking how adoption as of time *t* by other vendors affects own-adoption in time *t*, we could also ask how adoption as of time *t-1* by other vendors affects own-adoption in time *t*. The specification in column (4) lags the adoption variables to only consider merchants who adopted by time *t-1*. The social variables (social competitors and social non-competitors) are not significant, but the strong and significant association of own-adoption with adoption by non-social non-competitors and non-social competitors remains.

The specific definition of time periods and lags could influence our results. To rule out this possibility, we create a cross-section dataset in which we redefine each key variable according to the period when the merchant adopted mobile money. For example, the social competitor variable for vendor *i* represents the share of social competitors that adopted mobile money before or in the same period that the merchant did, regardless of the period in which vendor *i* adopted electronic money. For merchants who never adopted mobile money, we use their most recent information (period seven). Since the data are now in cross-section, we control as well for time-invariant vendor and market dummy variables.[7]

The key variables of interest in Table 7 are now the share of all vendors in the market who adopted mobile money by the time vendor *i* had adopted (if ever); the share of social competitors, non-social competitors, and social non-competitors. We exclude non-social non-competitors. The interpretation of the market variable is now: compared to the influence of adoption by the disaggregated categories on own-adoption, what is the influence of the share of adoption among all market vendors? It is uniformly negative: vendors are more influenced by adoption by competitor or social peers.[8]

Table 7 reports estimates of several specifications that includes different combinations of time-invariant controls. The column (1) specification controls for time-invariant vendor and market characteristics. Adoption by social and non-social competitors continues to exert a significant influence on own-adoption. Consistent with previous research on the adoption of mobile money, age is negatively correlated with mobile money adoption and education is positively correlated with it. Vendors who live with someone between 15 to 50 years old (potentially more digitally literate) and who are less risk-adverse are also more likely mobile money adoption.

Column (2) controls for three other factors that might motivate vendors to adopt mobile money. These are captured by three dichotomous variables: (i) the vendor has relatives/friends outside the market who use mobile money, (ii) the vendor has been contacted by a mobile money promoter, and (iii) customers have asked to pay with mobile money. None of their coefficients are statistically significant, which suggests they do not play a key role in mobile money adoption. However, since we have no information on the timing of contact with a promoter or of customer requests relative to the decision to adopt, we do not draw strong inferences from these results. Instead, we are reassured that the coefficient on non-social competitors remains large and significant and the others, though not significant, change little in magnitude from the regressions in Column (1).

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[7] We lose 13 vendors in the cross-section. Some of the vendors' relatives/friends were peddlers (*ambulantes*); they sold in or around the market, but did not own a stand. Hence, they were not included in our census. In addition, some vendors refused to answer the questionnaire in the first round. We were still able to collect the mobile money adoption information from these individuals, but we were not able to collect other detailed information such as financial inclusion or risk aversion.

[8] The market rate of adoption is also strongly correlated with market fixed effects. Those vendors who are reluctant to adopt even after controlling for all other market and vendor characteristics are least likely to be moved to adopt by high rates of market adoption.

Table 7. Cross-section model

	(1)	(2)	(3)
VARIABLES	Time invariant variables	External exposure	Network effects
Market	-0.387***	-0.375***	-0.377***
	(0.0407)	(0.0433)	(0.0445)
Social competitors	0.0328*	0.0317	0.0548**
	(0.0191)	(0.0193)	(0.0227)
Non social competitors	0.0586**	0.0572**	0.0561**
	(0.0236)	(0.0232)	(0.0269)
Social non competitors	-0.00143	-0.00417	0.0314
	(0.0270)	(0.0265)	(0.0316)
Market 2 dummy	-0.717***	-0.679***	-0.700***
	(0.0842)	(0.0946)	(0.0965)
Market 3 dummy	-1.226***	-1.166***	-1.237***
	(0.0920)	(0.124)	(0.105)
Female	-0.00114	-0.00935	-0.00631
	(0.0448)	(0.0450)	(0.0495)
Age	-0.00362*	-0.00349*	-0.00465**
	(0.00197)	(0.00198)	(0.00206)
Education level (high school)	0.151***	0.143***	0.166***
	(0.0539)	(0.0546)	(0.0562)
Education level (more than high school)	0.122*	0.116*	0.113
	(0.0674)	(0.0697)	(0.0733)
Weekly customers (log)	-0.0380	-0.0402	-0.0346
	(0.0270)	(0.0272)	(0.0287)
Has smartphone with internet	0.0344	0.0228	0.0121
	(0.0664)	(0.0685)	(0.0676)
Lives with someone between 15-50	0.105*	0.0950*	0.124**
	(0.0558)	(0.0558)	(0.0583)
Uses at least one financial service	0.0553	0.0449	0.0693
	(0.0553)	(0.0558)	(0.0584)
Risk aversion index	0.0669***	0.0637***	0.0687***
	(0.0215)	(0.0216)	(0.0211)
Has double stand	0.0425	0.0500	0.0302
	(0.0513)	(0.0517)	(0.0543)
Works with someone between 15-50	-0.0228	-0.0184	-0.0239
	(0.0512)	(0.0521)	(0.0536)
Has relatives/friends outside the market who have adopted		0.0200	
		(0.0567)	
Has been contacted by mobile money promoter		0.0197	
		(0.0635)	
Clients have asked to pay with mobile money		0.0382	

	(1)	(2)	(3)
		(0.0734)	
Network: % women			-0.0344
			(0.0849)
Network: average age			0.000688
			(0.00361)
Network: Less than high school			0.363
			(0.417)
Network: Completed high school			0.366
			(0.408)
Network: Beyond high school			0.352
			(0.415)
Network: Weekly customers (log)			-0.115**
			(0.0541)
Network: Has smartphone with internet access			-0.0593
			(0.117)
Network: Lives with someone between 15-50 years			-0.126
			(0.107)
Network: Uses at least one financial service			-0.0160
			(0.0835)
Network: Risk aversion index			0.119**
			(0.0493)
Network: Doubled size stand			0.0151
			(0.0988)
Network: Has assistant between 15-50 years			0.112
			(0.113)
Constant	1.254***	1.222***	1.352***
	(0.198)	(0.218)	(0.214)
Observations	279	278	265
R-squared	0.605	0.609	0.629
Market dummies	YES	YES	YES
Category dummies	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

All estimates control for adoption within vendors' social networks, but do not control for the specific characteristics of those networks. These characteristics, more than the networks themselves, may influence adoption. The column (3) specification therefore controls for the average values, among members of the vendor's network, of 12 variables, ranging from their age and gender to their level of risk aversion and use of financial services. The main results are unchanged: adoption by social and non-social competitors continues to drive own-adoption. Two characteristics of network members also are significantly related to own-adoption. Vendors whose social network includes more risk-loving individuals are also more likely to adopt mobile money, even controlling for their own level of risk aversion. More puzzling is the relationship between number of customers and adoption. At the individual level, the number of weekly customers reported by vendors has an insignificant, but negative relationship with adoption probabilities. At the social network level, this negative correlation becomes significant: the more customers their network members report, the less likely are vendors to adopt mobile money.

Conclusions

Small firms and microenterprises proliferate in developing countries, and in Peru particularly. Their persistent low productivity therefore has significant negative implications for growth and incomes. One solution to this is to facilitate the reallocation of factors of production out of these firms into more productive, larger firms. Numerous policy and market failures hinder this reallocation, however.

An alternative approach to mitigating the problem is to encourage productivity-upgrading by incumbent small firms and microenterprises. These often revolve around extension-type services and training to inform firms of the benefits of productivity improvements they could make. Social learning can enhance the effectiveness of these programs, and promote technology adoption in general, by providing credible evidence to firms of the value and risks associated with adoption.

Evidence from Peruvian food markets indicates that social learning supports technology adoption, as in previous research. However, competition between microenterprises has an even more robust effect. It suggests that government policies could usefully take into account potential barriers to competition among small and micro enterprises as a way to accelerate productivity growth among these firms.

References

Agranov, Marina, Gabriel Lopez-Moctezuma, Philipp Strack and Omer Tamuz (2022). "Learning Through Imitation: An Experiment." NBER Working Paper 29962.

Banerjee, Abhijit V. (1992). "A simple model of herd behavior." *The Quarterly Journal o Economics* 107:3, 797-817.

Agarwal, S., W. Qian, B. Y. Yeung, and X. Zou (2019). "Mobile wallet and entrepreneurial growth." *American Economic Association Papers and Proceedings*. 109: 48–53

Agrarwal, Sumit, Wenlan Qian, Yuan Ren, Hsin-Tien Tiffany Tsai, and Bernard Yin Yeung (2020). "The Real Impact of FinTech: Evidence from Mobile Payment Technology." (March 18). Available at SSRN: https://ssrn.com/abstract=3556340 or http://dx.doi.org/10.2139/ssrn.3556340

Aker, Jenny C. and Isaac M. Mbiti (2010). "Mobile Phones and Economic Development in Africa." *Journal of Economic Perspectives* 24:3, 207-32.

Aker, Jenny C., Rachid Boumnijel, Amanda McClelland, and Neiall Tierney (2016). "Payment Mechanisms and Antipoverty Programs: Evidence from a Mobile Money Cash Transfer Experiment in Niger." *Economic Development and Cultural Change* 65:1, 1-37.

Alidaee, Hossein (2023). "How Uncertainty About Heterogeneity Impacts Technology Adoption." Mimeo, Northwestern University.

Bandiera, Oriana and Imran Rasul (2006). "Social networks and technology adoption in northern Mozambique." *Economic Journal* 116:514, 869-902.

Bian, Wenlong, Lin William Cong and Yang Ji (2023). "The Rise of E-Wallets and Buy-Now-Pay-Later: Payment Competition, Credit Expansion, and Consumer Behavior." NBER Working Paper 31202.

Conley, Timothy G. and Christopher R. Udry (2010). "Learning about a New Technology: Pineapple in Ghana." *American Economic Review* 100:1, 36-69.

Crouzet, Nicolas, Apoorv Gupta, and Filippo Mezzanotti (2023). "Shocks and Technology Adoption: Evidence from Electronic Payment Systems." *Journal of Political Economy* 131:11, 3003-3065.

Cusolito, Ana Paula, Alvaro Garcia-Marin, and William F. Maloney (2023). "Proximity to the Frontier, Markups, and the Response of Innovation to Foreign Competition: Evidence from Matched Production-Innovation Surveys in Chile." *American Economic Review: Insights* 5:1, 35-54.

de Mel, Suresh and McKenzie, David John and Woodruff, Christopher, Innovative Firms or Innovative Owners? Determinants of Innovation in Micro, Small, and Medium Enterprises (May 1, 2009). World Bank Policy Research Working Paper No. 4934, Available at SSRN: https://ssrn.com/abstract=1407952

Foster, Andrew D. and Mark R. Rosenzweig (2010). "Microeconomics of Technology Adoption." *Annual Review of Economics* 2:395-424.

Goolsbee, A. and P. J. Klenow (2002). "Evidence on learning and network externalities in the diffusion of home computers." *The Journal of Law and Economics* 45:2, 317–343.

Helpman, Elhanan (2023). "Foreign Competition and Innovation." NBER Working Paper No. 31840.

Ilzetzki, (2023). "Learning by Necessity: Government Demand, Capacity, Constraints, and Productivity Growth." Mimeo, London School of Economics.

Jack, William and Tavneet Suri (2014). "Risk sharing and transaction costs: Evidence from Kenya's mobile money revolution." *American Economic Review* 104:1, 183-223.

Krishnan, Pramila and Manasa Patnam (2014). "Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption?" *American Journal of Agricultural Economics* 96:1, 308-327.

Lee, Jean N., Jonathan Morduch, Saravana Ranvindran, Abu Shonchoy, and Hassan Zaman (2021). "Poverty and Migration in the Digital Age: Experimental Evidence on Mobile Banking in Bangladesh." *American Economic Journal: Applied Economics*. 13:1, 38-71.

Machokoto, Michael, Daniel Gyimah, and Collins G. Ntim (2021). "Do peer firms influence innovation?" *The British Accounting Review* 53:5, 100988.

Macher, Jeffrey T., Nathan H. Miller, and Matthew Osborne (2021). "Finding Mr. Schumpeter: technology adoption in the cement industry." *RAND Journal of Economics*. 52:1, 78-99.

Maertens, Annemie and Christopher B. Barrett (2012). "Measuring Social Networks' Effects on Agricultural Technology Adoption." *American Journal of Agricultural Economics* 95:2, 353-359.

Millou, Chrysovalantou ad Emmanuel Petrakis (2011). "Timing of Technology Adoption and Product Market Competition." *International Journal of Industrial Organization* 29:5, 513-23.

Nakano, Yuko, Takuji W. Tsusaka, Takeshi Aida, and Valerien O. Pede (2018). "Is farmer-to-farmer extension effective? The impact of training on technology adoption and rice farming productivity in Tanzania." *World Development* 105, 336-351.

Oster, Emily and Rebecca Thornton (2012). "Determinants of Technology Adoption: Peer Effects in Menstrual Cup Take-Up." *Journal of the European Economic Association* 10:6, 1263-1293.

Riley, Emma (2018). "Mobile money and risk sharing against village shocks." *Journal of Development Economics* 135: 43-58.

Suri, Tavneet (2017). "Mobile Money." *Annual Review of Economics* 9, 497-520.

_____ and William Jack (2016). "The long-run poverty and gender impacts of mobile money." *Science*. 354:6317, 1288-1292.

Takahashi, Kazushi, Yukichi Mano, and Keijiro Otsuka (2019). "Learning from experts and peer farmers about rice production: Experimental evidence from Cote d'Ivoire." *World Development* 122: 157-169.

Vasilaky, Kathryn N. and Asif M. Islam (2018). "Competition or cooperation? Using team and tournament incentives of learning among female farmers in rural Uganda." *World Development* 103: 216-225.

Zuniga Lara, Maria Pluvia and Benavente, Jose Miguel, How Does Market Competition Affect Firm Innovation Incentives in Emerging Countries?. Available at SSRN: https://ssrn.com/abstract=4095801 or http://dx.doi.org/10.2139/ssrn.4095801