Seeding the Technology S-Curve?
The Role of Early Adopters in Technology Diffusion

Christian Catalini and Catherine Tucker

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Abstract

In October 2014, all 4,494 undergraduates at the Massachusetts Institute of Technology were given access to Bitcoin, the first decentralized digital currency to solve the problems that had plagued computer scientists' early attempts at creating digital cash. As a unique feature of the experiment, students who would generally adopt only mature and established technologies were placed into an early-adopter condition: suddenly they had to decide to either learn more about Bitcoin and try to use it, to bet on its volatile future by holding it, or to simply cash out and convert it into US dollars. In this paper, we explore the students' response to the digital currency, and in particular how randomly delaying different types of students relative to their peers affected their adoption decision. Our results point to a novel mechanism through which early-adopters may influence technology adoption, and ultimately technology S-curves: whereas the existing literature has stressed the positive, network-effect building role of individuals who seek early adopter status, our data suggests that they can also be an obstacle to diffusion. If early-adopters derive consumption utility from being first among their peer group in embracing new technology trends, excluding them from early access has a strong effect on the likelihood that they will ignore the technology. Moreover, their behavior seems to generate negative spillovers on adoption by their peers. The experimental nature of our data, combined with fine-grained information about individual outcomes, allows us to cleanly estimate the causal effect of short delays on adoption. Small changes in the initial availability of a technology among different types of users have a lasting effect on its potential: Seeding a technology while ignoring early adopters' needs for distinctiveness is counterproductive.

1 Introduction

In October 2014, students at the Massachusetts Institute of Technology were preparing for one of the largest social science experiments the campus had seen: in the following weeks, every undergraduate student would be given $100 worth of Bitcoin, the first decentralized cryptocurrency to solve the double-spending problem that had plagued computer scientists' early attempts at creating digital cash (Nakamoto 2008, Narayanan, Bonneau, Felten, Miller, and Goldfeder 2016). Whereas a small number of Bitcoin enthusiasts were describing a future where the borderless digital currency would replace fiat currencies and drastically change every aspect of the financial industry, immediate use cases (and users) were very limited, making it an ideal context for studying the early stages of technology adoption. Bitcoin's extremely high volatility[1] was a clear reflection of its experimental nature and of how even insiders had a difficult time assessing its value, if it would diffuse further, disappear or eventually be replaced by a better implementation of the same cryptographic ideas.

A unique feature of our research design was that it pushed students who would generally adopt a technology only once it is mature and established into an early-adopter condition: suddenly they had to decide to either learn more about Bitcoin and try to use it, to bet on its volatile future by holding it, or to simply cash out and convert it to US dollars. In this paper, we explore the students' response to the digital currency, and in particular how randomly delaying different types of students relative to their peers affected whether or not they abandoned the technology. Our results point to a novel mechanism through which early-adopters may influence technology adoption or abandonment: whereas the existing literature has stressed the positive, network-effect building role of individuals who seek early adopter status, our data highlight a situation where those who naturally adopt technologies early become an obstacle to diffusion. If early-adopters derive consumption utility from being first among their peer group in embracing new technology trends (or tie their identity and reputation to it), excluding them from early access has a strong effect on the likelihood that they will abandon the technology.

After exploring why delaying early-adopters increases their rate of abandonment, we test if their

[1] The price went from 14$ at the beginning of 2013 to a peak of 1,147$ in December 2013, and then back to 214$ in early 2015.

behavior generates long-lasting spillovers on their peers by looking at technology abandonment curves: dorms and social clusters where an above the median share of early-adopters is delayed, are characterized by a substantially faster decline in adoption, which is consistent with early-adopters slowing down further diffusion.

The literature on innovation diffusion (Griliches 1957, Rogers 1962, Jensen 1982, Mansfield and Mansfield 1993) and on technology S-curves (Henderson 1988, Henderson 1995, Henderson and Clark 1990, Christensen 1992) places a strong emphasis on the role early-adopters play in defining: (a) the success of a new innovation, and (b) the speed at which it diffuses through social contagion in the economy. Early-adopters are typically individuals who receive higher initial benefit from adoption either because of their idiosyncratic preferences or because of how the technology positively affects their productivity. As a result, they are more likely to embrace a technology when the costs of using it are still relatively high. Once the innovation matures, adoption costs drop due to economies of scale and the development of complementary technologies, expanding the set of individuals, firms and institutions that find switching to the new technology optimal.

Early-adopters can influence their peers through rational, observational learning (Banerjee 1992, Vives 1993, Glaeser, Sacerdote, and Scheinkman 1996, Bikhchandani, Hirshleifer, and Welch 1998) or through social influence (Katz and Lazarsfeld 1955, Fisher and Price 1992, Watts and Dodds 2007). Complicating this process though is the need to balance a potential early adopter's need for conformity versus differentiation (Brewer 1991, Leonardelli, Pickett, and Brewer 2010, Chan, Berger, and Van Boven 2012, Zuckerman 2015). Seeding a new technology, while ignoring the needs of potential early adopters to be distinctive, is therefore unlikely to generate an optimal adoption cascade, as the ability to influence or be influenced by others varies by individual and context.

On the MIT campus, the natural process of social contagion was affected by the order in which students received their bitcoin: because of the random assignment of individuals to a distribution cohort, some early-adopters had to wait for two additional weeks, whereas some naturally late-adopters were placed in the unfamiliar situation of being among the first to hold the digital currency. In the paper, we rely on this source of exogenous variation to study how the delay affected outcomes for different students. Since the technology was exogenously introduced and everyone was temporarily turned into a user (to participate, students had to create and secure their own digital wallet), we focus on the students' decision to revert our intervention, i.e. to disadopt or abandon Bitcoin. We interpret this action of opting out as evidence that the students involved preferred traditional, fiat-money to their recently acquired cryptocurrency.

Because of the way social influence can accelerate (or stifle) adoption, startups and high-tech firms pay particular attention to lead users when seeding new products: not only do these customers have a higher tolerance for defects and their feedback can be instrumental in building a product for the mass market (Von Hippel 1986, Von Hippel 2005), but they also help form the opinion of others. As a result, firms strategically manage the availability of a new product in order to maximize its chances of success. A common solution to the seeding problem is to rely on a waiting list to identify lead users: individuals that are more eager to try a new product sign up first, revealing in the process their early-adopter nature. Probably the most recent, successful example of a waiting list approach was the one used by Google in the rollout of Gmail: faced by capacity constraints (the promise of 1GB of email storage was unprecedented for 2004), the company decided to seed adoption by offering Gmail to a few thousand outsiders, who would then be able to select the next batch of users through personal invites. The social nature of the process, combined with the unintentional exclusivity coming from the limited capacity and invitation waves, transformed Gmail into a sought status symbol among the tech crowd, with invites for the free service being sold on Ebay for more than $150. In recent years, crowdfunding platforms (e.g., Kickstarter, Indiegogo) have institutionalized the seeding process by capitalizing on early-adopters' higher willingness to pay for early access (i.e., for a spot on the waiting list) to directly fund the development of early-stage projects (Agrawal, Catalini, and Goldfarb 2013).

2 Empirical Setting and Data

Our focus is on technology abandonment, i.e. on who gave up on Bitcoin. We identify perturbations to the natural order of adoption by relying on the random assignment of students to one of our two distribution cohorts. 50% of participants was randomly delayed relative to their peers by 2 weeks, and no one was informed about when they would receive their bitcoin, nor explanation was given for why some students received it and others did not. As a result, some natural early-adopters were randomly not allowed to be first to adopt.

In our experiment, we rely on the order in which students signed up for the bitcoin distribution (i.e., on a waiting list) to identify those who would naturally seek early adopter status. The first 777 students that registered with us (top 25% of our sample) are classified as early-adopters.[2] The process is analogous to how startups progressively deliver access to new users when faced with capacity constraints (e.g. Gmail, Google Glass, Mailbox etc.). Survey measures corroborate our "revealed preferences" approach to identifying early-adopters: the first students on the waiting list are more likely to be top coders, to be financially independent, to use new payments apps like Venmo or Square Cash on a weekly or daily basis, to place more trust than their peers in tech firms and startups for their financial services (Figures A-1a to A-1g).

Our outcome of interest is if students cashed out their bitcoin within two weeks from receiving them (disadoption), or decided to keep them for longer. An unusual feature of our setting is that abandonment actually has an upside (not a sunk cost), and therefore one may worry that the first students to register were simply cash constrained and had no interest in Bitcoin, i.e., that they rushed to sign up only to convert their digital tokens into dollars: to rule out this alternative explanation, in the appendix (Figure A-2) we show that our main results are stronger, not weaker, when we focus only on students that are more likely to be financially independent (e.g., have a credit card for discretionary purposes, had a paying job over the summer).[3]

To track usage and cashing out, we obtain transaction data directly from digital wallet providers and, for participants who do not use an intermediary (e.g. because they use an open-source digital wallet like Electrum), from the Bitcoin blockchain (the public, digital ledger that records every transaction between Bitcoin users). Our measure of cashing out based on transaction data is consistent with students' responses regarding technology abandonment in the final survey (Figure A-4a). Moreover, our main result is robust to limiting the sample to digital wallets for which we have a perfect information on identity (as financial intermediaries need to comply with Anti-Money

[2] Results are robust to more stringent definitions, e.g. top 15% or top 10% of the waiting list.

[3] We also do not observe any systematic difference between students that carry above versus below the median cash in their wallets, see Figure A-3.

Laundering and Know Your Customer regulations, Figure A-4b), and to excluding anyone who used Bitcoin before (Figure A-4c).

We complement transaction data with survey information coming from our registration process, as well as intermediate and final surveys (which cover social network information, attitude towards Bitcoin and other fintech technology, spending patterns and preferences etc.). Demographic information is provided by the Institutional Research section of the MIT Office of the Provost. 70% of eligible undergraduate students participated in the study (the online registration process and survey required between 15 to 45 minutes) and, relative to the overall MIT population, our sample is slightly more likely to be male, a US citizen, to be majoring in Electrical Engineering and Computer Science (Course 6), and to be enrolled in the first three years of the program.

Whereas we present our main results from the randomizations using simple graphs and splits of the data, we show robustness in the appendix using regressions. The econometric analysis uses cross-section, Logit regressions at the user level with robust standard errors where we estimate variations of:

$$Y_i = \beta_1 EarlyAdopter_i + \beta_2 Delayed_i + \beta_3 DelayedEarlyAdopter_i + R_i + X_i + \epsilon_i \quad (1)$$

Where Y_i is a dummy for cashing out within two weeks from receiving bitcoin, $EarlyAdopter_i$ is a dummy equal to 1 if the student is classified as an early-adopter according to our waiting list, $Delayed_i$ is a dummy equal to 1 if the student was randomly delayed by two weeks, and $DelayedEarlyAdopter_i$ is an interaction of the other two terms. R_i is a vector of controls for other randomizations the focal participant was part of, and X_i is a vector of student characteristics (e.g. dorm assignment, software development skills, digital wallet used, expectations about future Bitcoin price etc.). ϵ_i is an idiosyncratic error term.

3 Results

3.1 Main Result

Figure 1 presents the main result of the paper: whereas most students are indifferent to receiving their bitcoin early or after two weeks (9.8% cashes out within two weeks when not delayed, and 9.6% when delayed, p=0.8653), early-adopters almost double their cash out rate when delayed (from 10.8% to 18.3%). The 7.5% difference is statistically significant (p=0.0033) and suggests that delaying early-adopters may have a strong, negative effect on overall technology diffusion, specially if we believe that these individuals could influence others in the future.

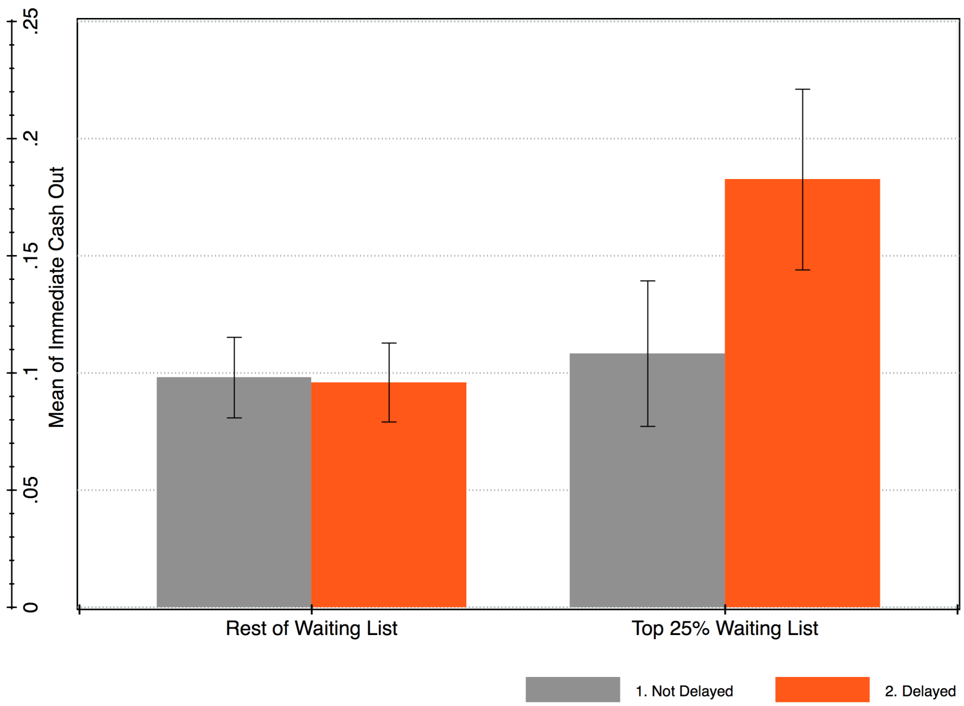


Figure 1: Delaying Early Adopters Increases Their Cash Out Rate

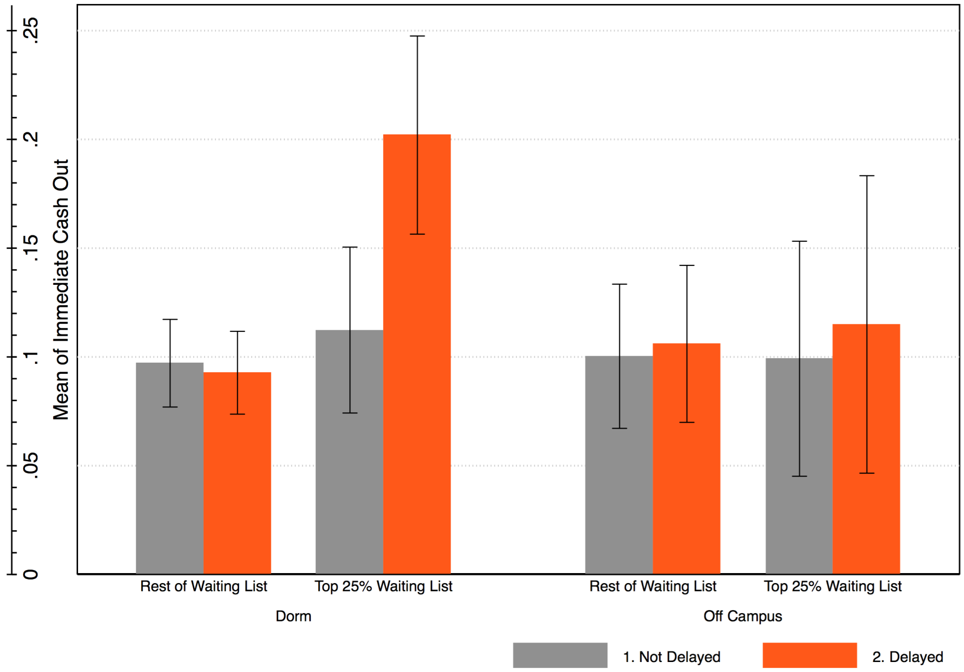
3.2 Understanding the Mechanism

The traditional explanation for the effect is that by delaying early-adopters the randomization has limited the ability of others to properly learn from them (either directly or through observation): i.e., by the time early-adopters receive their bitcoin, the adoption process has unraveled, leaving them with no option but to abandon the technology. The key piece of evidence that is consistent with this interpretation is that the result is more pronounced for early-adopters with the strongest technical skills (their cash out rate increases from 8.8% under no delay, to 18.5% with a delay, p=0.014, see Figure A-5), although one could also argue that the same skills are required for being recognized as an early-adopter and technology influencer among your peers in the first place.[4]

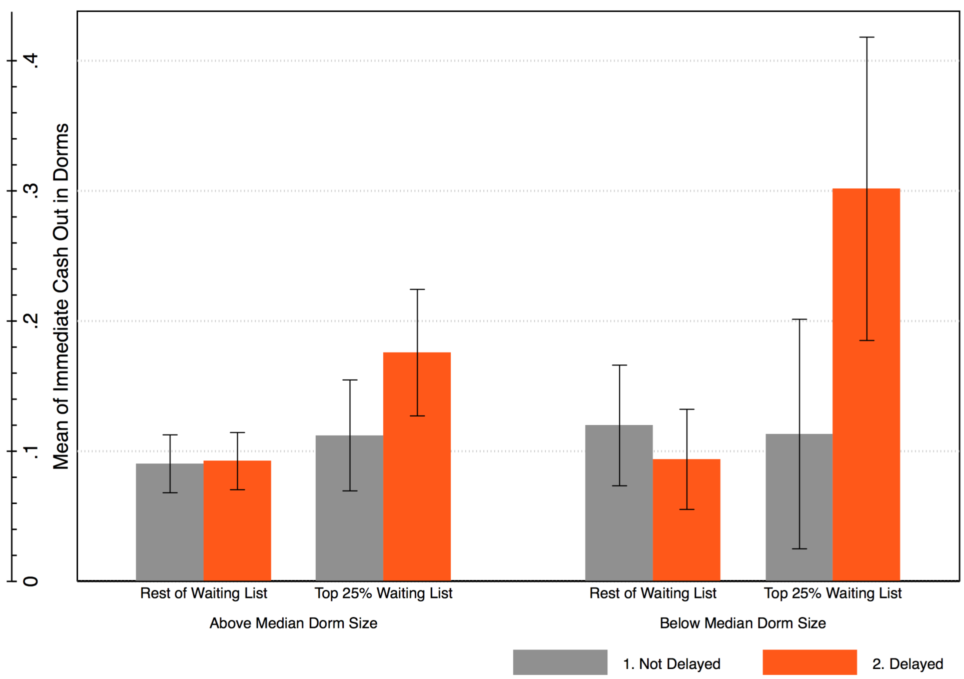
The negative response by delayed early-adopters seems to be social in nature: the effect disappears for students that are living off campus (Figure 2a), and is substantially more pronounced within smaller dorms (Figure 2b), where the observability of one's delay is likely to be stronger. Results are robust to the inclusion of a number of controls such as the location of the dorms on campus, the digital wallets selected by the students, the absence of past experience with Bitcoin, students' technical skills and expectations about the future price of Bitcoin (see Table A-1 in the appendix).

Whereas smaller dorms are also the ones where one would imagine learning from peers to be potentially more effective (as the smaller dorm size may favor interactions and better observability), Figures 2(a) and 2(b) also support an alternative explanation: if early-adopters tie their identity to being first among their peer group in embracing new technology trends, then the delay could be seen as a challenge to their reputation as technology gatekeepers within these densely connected communities, or could reduce the consumption utility they derive from adoption. By immediately cashing out, delayed early-adopters are essentially moving on and not endorsing the technology, which leaves their reputation as lead users unaffected. Even in the absence of reputation effects, if the delay is long enough to reduce the utility early-adopters' derive from early-access (i.e. from an exclusivity period), then we would expect higher abandonment, as at the margin some early-adopters will now find cashing out optimal.

[4]Unfortunately, the number of early-adopters with no coding skills is very small (59), so we are unable to separate what fraction of the effect is due to early-adopters having technical skills or not. Early-adopters represent 18.8% of non coders versus 30.7% of top coders.



(a) Dorms versus Off Campus



(b) Small versus Large Dorms

Figure 2: Dorms

Figure 3 presents evidence that is consistent both with the reputation and consumption utility hypothesis as well as with the learning one: cashing out is higher in environments where early-adopters are more likely to be scarce and unique (below median density of computer science students), and statistically insignificant where multiple technological leaders are likely to co-exist (above median density of computer science students). Results are robust to alternative definitions based on the density of pre-existing Bitcoin users, top coders or other early-adopters (see Table A-2 in the appendix). Since dorms with a higher density of computer science students are also those were learning from peers is less likely to be important (as most students will have the right technical skills to understand and use Bitcoin), Figures 1 to 3 do not allow us to directly separate learning effects from reputation effects.

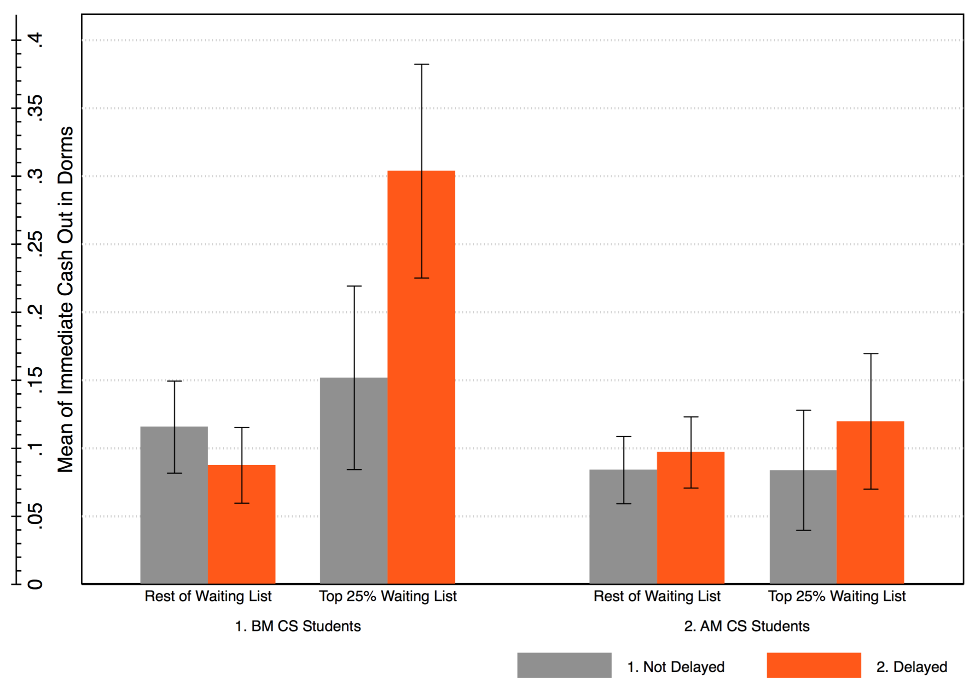


Figure 3: Density of Computer Science Students in Dorms

One way to directly test if delayed early-adopters have higher cash out rate because of their inability to jumpstart network effects among their peers through learning is to look at the case where they are delayed, but so is their peer group. Under this condition, the entire social circle is delayed, and the "diffusion clock" is essentially shifted by two weeks. If one believes peer-effects and learning to be the dominant mechanism at work, then one should expect early-adopters to not increase their cash out rate under this treatment, as their delay does not limit their ability to teach others about the technology.

Figure 4 shows us that this is not the case: when everyone is delayed, early-adopters have a 10.9% higher cash out rate than other users (p=0.0000). Interestingly, when nobody is delayed, early-adopters are indistinguishable from their peers (12.6% cash our rate versus 10.4%, p=0.1483). In the appendix (Figure A-6) we additionally show that early-adopters' cash out rate is high (14.2%) even when none of their friends has cashed out, which supports the idea that their decision is unrelated to the decision of their peers.

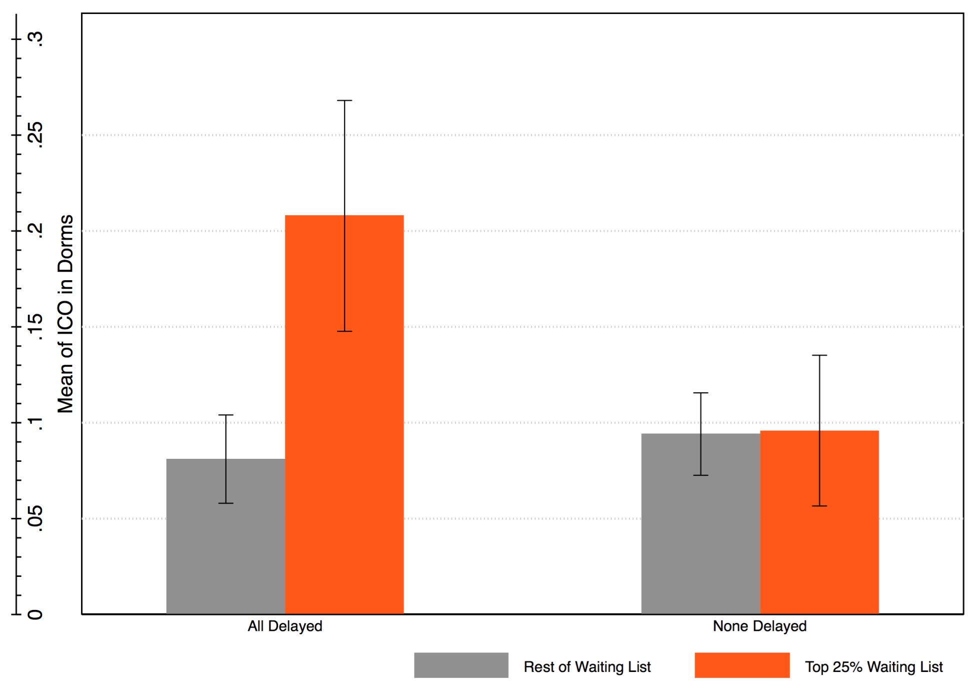


Figure 4: All Delayed versus None Delayed

One may worry that early-adopters are more informed and therefore better at predicting the Bitcoin price, or were able to extract more information about the future of the digital currency during the two weeks of the delay. While this would not explain why non-delayed early-adopters did not update their priors in a similar fashion[5], in Figure 5a we test if the share of participants

[5]Both cohorts received their $100 in bitcoin at very similar prices: $351 for the first cohort, and $355 for the

who revised down their expectations about the future price between our surveys[6] systematically differed between early-adopters and other users (delayed or not). We find no evidence of stronger updating for early-adopters, which is consistent with the effect of the delay not being driven by changes in expectations. In fact, our main effect is mostly driven by individuals who have stable or even positive updating about the price (see Figure A-7 in the Appendix).

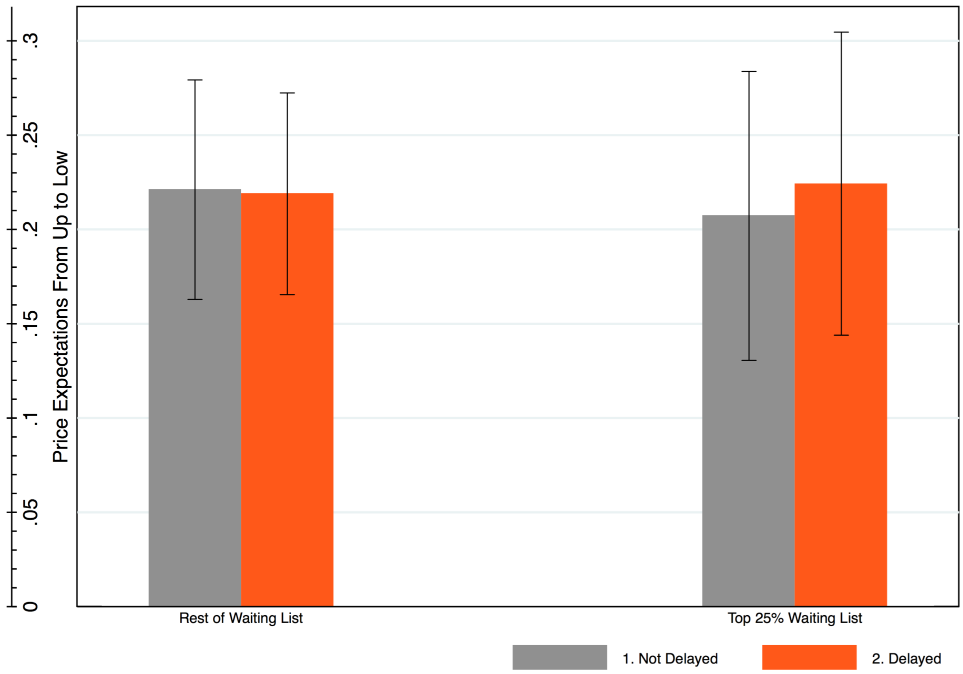
Early-adopters, moreover, do not cash out on average at better prices than other students (Figure 5b), which is not surprising given the high volatility of the digital currency during the study period. We also do not observe differences between students who were interested in Bitcoin as an investment vehicle or that were more risk averse[7] (see Figure A-8 in the Appendix).

Overall, we believe the results in Figures 1 to 5 support the idea that while learning and peer-effects may play a role in the decision of early-adopters to cash out when delayed, they are unlikely to explain the vast majority of the effect. Whereas it is possible that the groups where a larger share of early-adopters was delayed did not benefit from their technical support, it seems that the choice by early-adopters to cash out was a personal one, and was either tied to their desire to keep their reputation as technology gatekeepers intact, or due to a reduction in consumption utility (because of the lost exclusivity period).

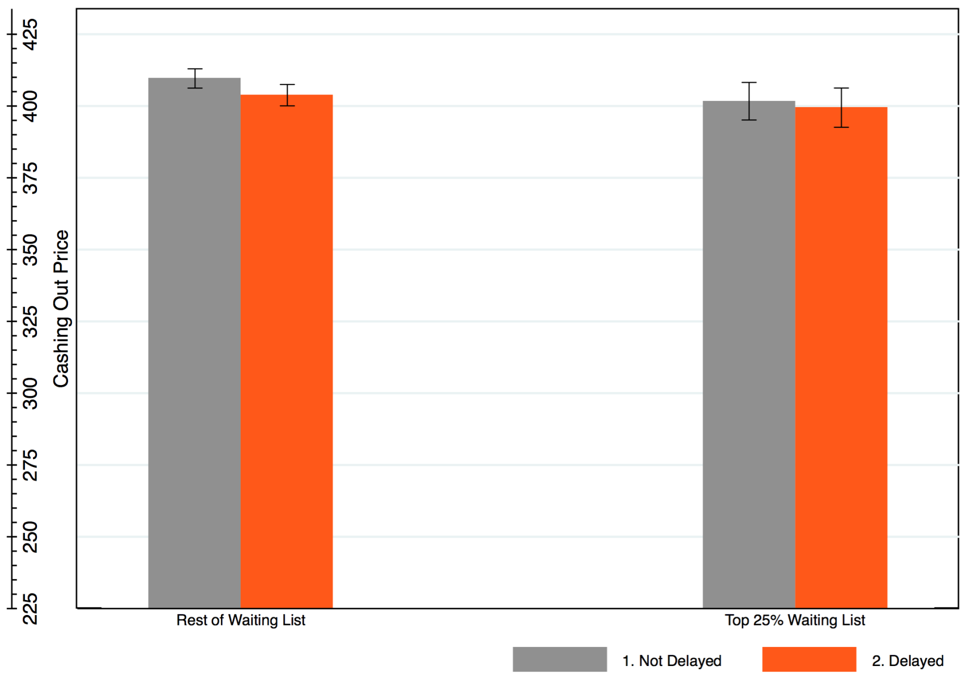
second.

[6]The first survey was part of the registration process and was therefore completed in November 2014 before the distribution of bitcoin, whereas the second was delivered online in May 2015.

[7]As proxied by their higher interest in deposit insurance for their digital currency wallet.



(a) Share of Participants who Revise their Price Expectation About Bitcoin from High to Low



(b) Average Bitcoin Price at Cash Out

Figure 5: Early-Adopters, Price Expectations and Bitcoin Price at Cashing Out

3.3 Technology Abandonment Curves

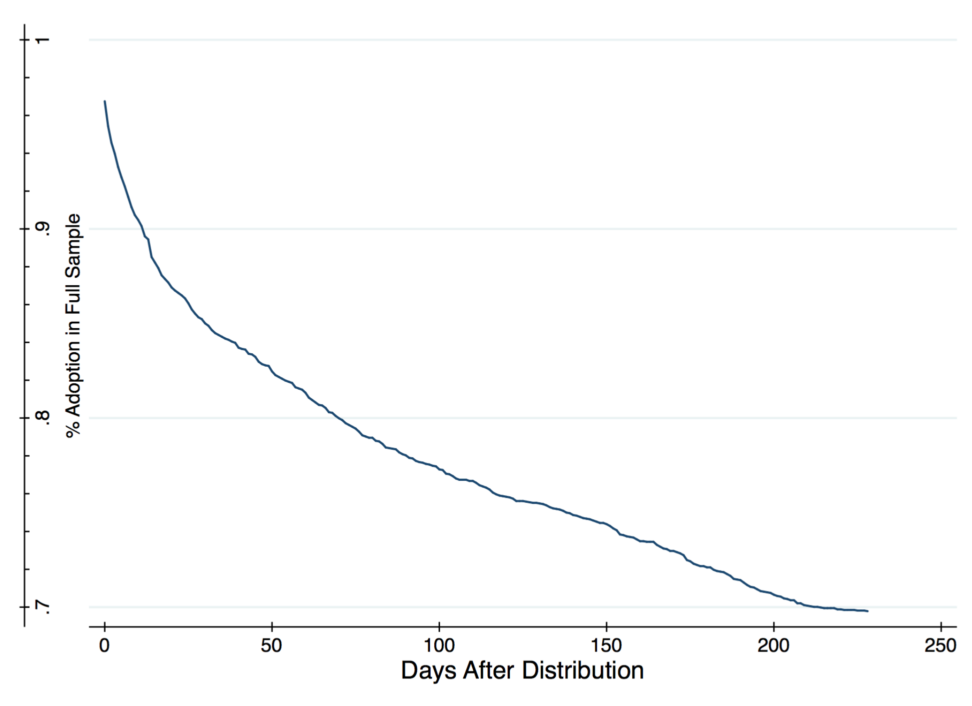
To test if abandonment by delayed early-adopters had repercussions on overall technology diffusion, in this final section we move away from studying immediate cashing out activity, and focus on the timing of abandonment across different subpopulations in our sample.

Figure 6(a) shows the aggregate adoption rate in the full sample, and Figure 6(b) splits the sample by early-adopters versus not and delayed versus not: whereas non-delayed early-adopters exhibit a similar pattern to other users (whether delayed or not), delayed early-adopters are characterized by a substantially faster decay in adoption (from 90% in the days immediately following the distribution to roughly 60% after 6 months).

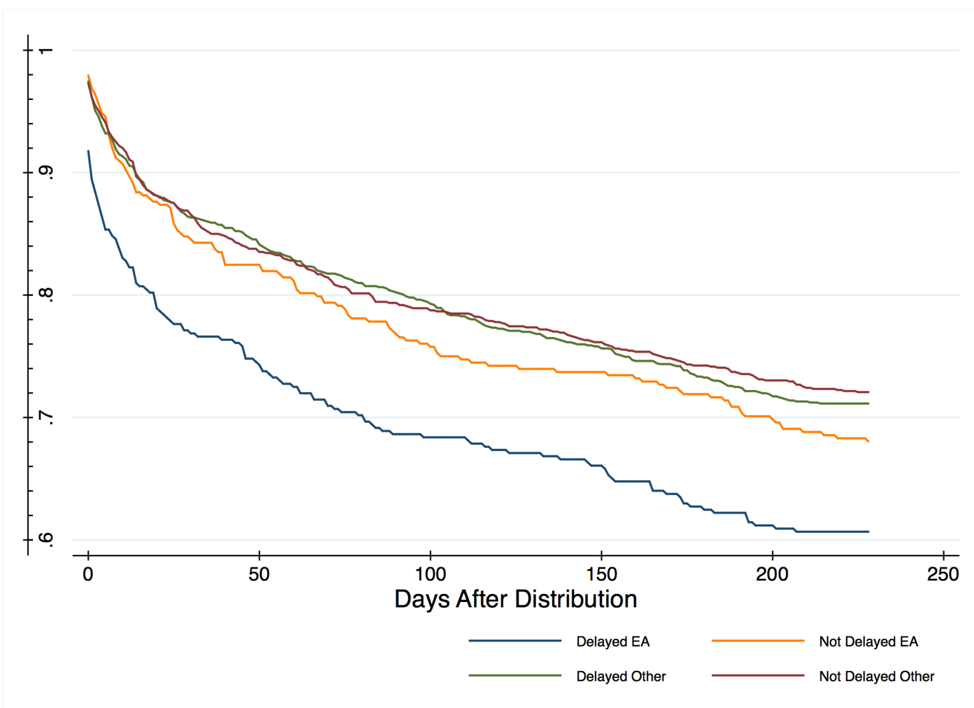
To see if early-adopters generated a negative spillover on their peers, Figure 7 only includes non early-adopters (NEA), and splits the sample by: 1) network clusters with an above the median versus below the median share of delayed early-adopters (Figure 7a); 2) dorms with with an above the median versus below the median share of delayed early-adopters (Figure 7b). Results are consistent with the presence of spillovers: the yellow lines, which represent network clusters or dorms with a larger share of delayed early-adopters, decay at a faster rate than the blue ones. Results are magnified when students are geographically proximate (small dorms, or same dorm and floor), possibly because the choices of early-adopters are potentially more visible when co-located (Figure 8).

In the Appendix, we additionally show how the abandonment curves do not change based on the students being financially independent versus not (Figure A-9a), their coding ability (Figure A-9b), living in a dorm versus off campus (Figure A-9c), and being surrounded by more versus less computer scientists (Figure A-9d).

Higher abandonment also corresponds to lower levels of activity: in Figure 9 we build technology S-Curves by calculating the share of active users (as captured by students who add funds to their digital wallet) over time. By the end of our observation period, dorms where a below the median share of early-adopters is delayed are 45% more active than other dorms.

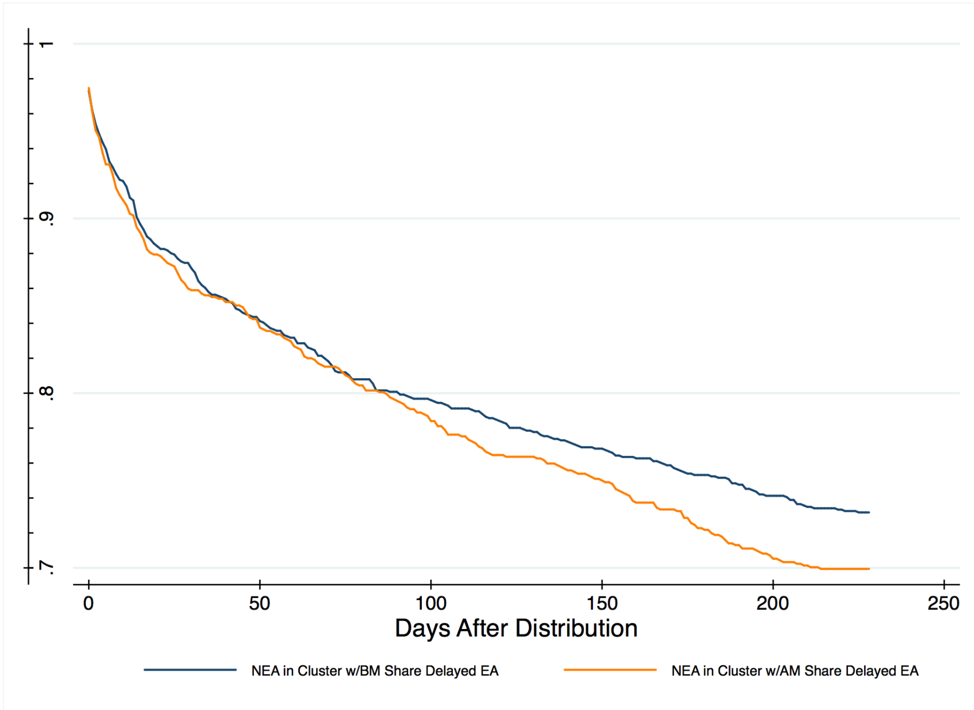


(a) Full Sample

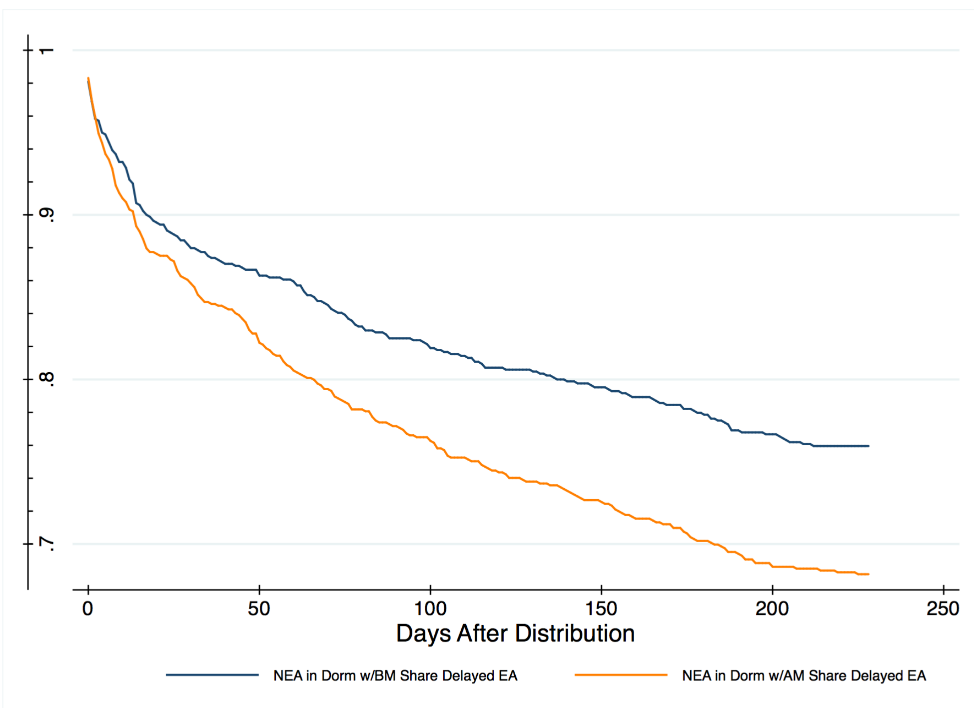


(b) Early Adopters versus Not, Delayed versus Not

Figure 6: Abandonment Curve

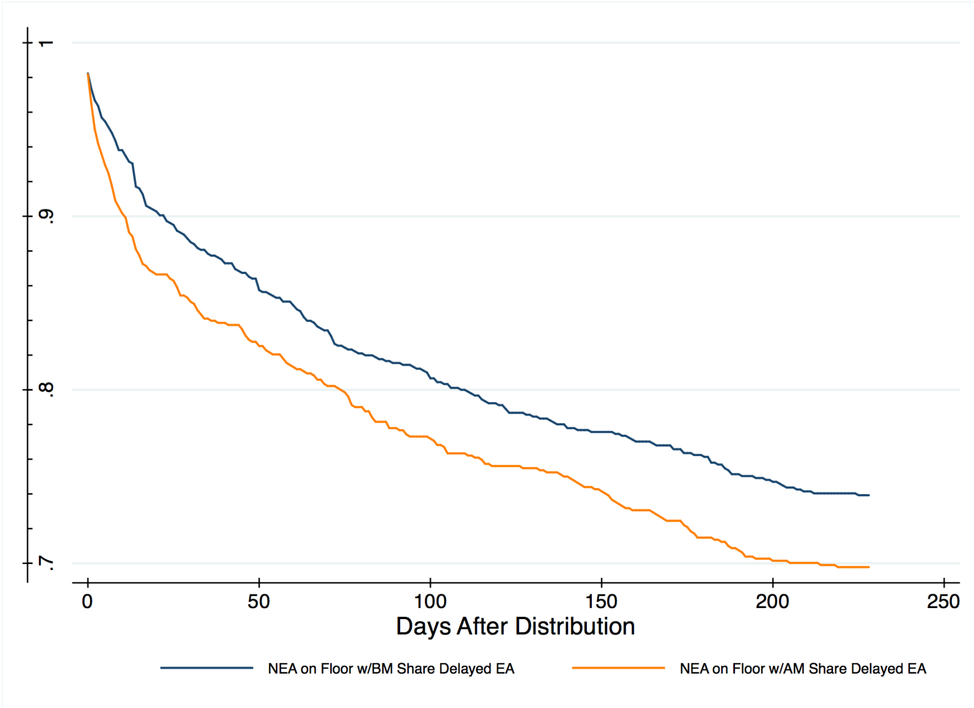


(a) By Network Clusters

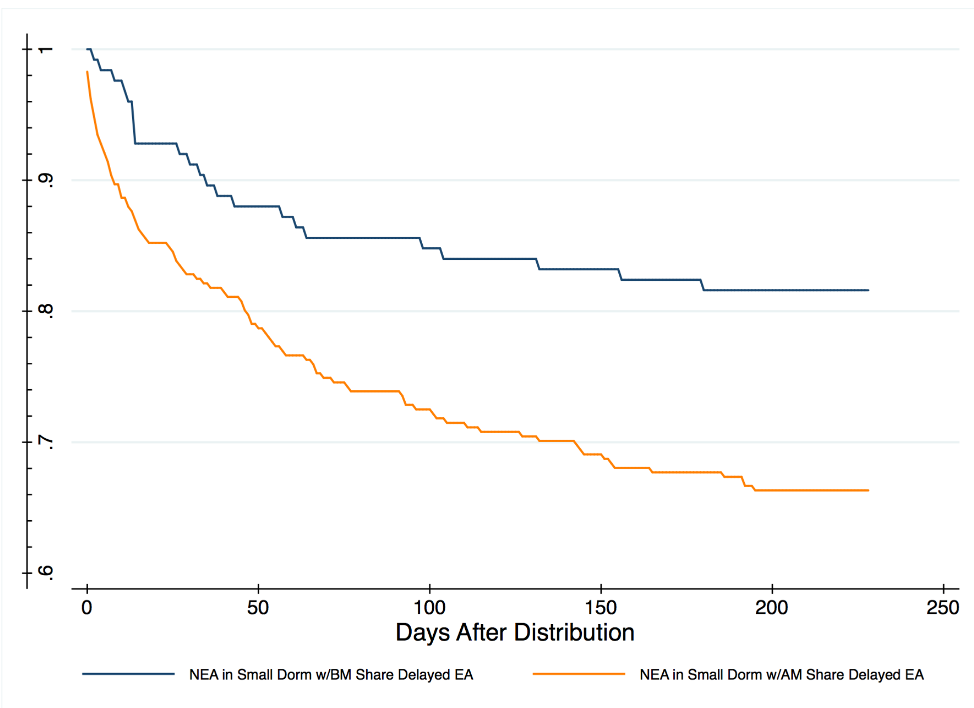


(b) By Dorms

Figure 7: Spillover Effects



(a) Dorm Floors



(b) Small Dorm

Figure 8: Spillover Effects and Microgeography

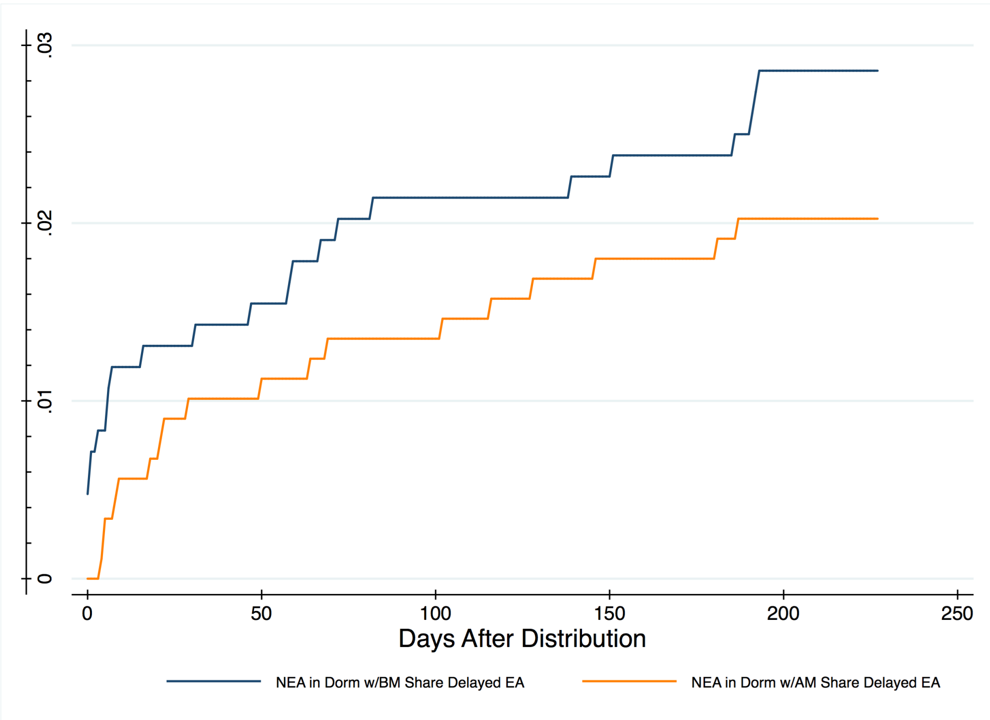


Figure 9: Technology S-Curves: Share Active (Received Additional Bitcoin)

4 Conclusion

The ability of an economy to generate, recombine, and diffuse innovations has a profound influence on its ability to sustain growth (Lucas 1988, Romer 1990, Weitzman 1998). At the same time, our understanding of the determinants of successful adoption is fairly limited: it can take decades for a new scientific breakthrough to be incorporated into a new technology, and even when scientific and technological uncertainty are resolved, an innovation still faces idiosyncratic challenges defined by the market, institutions and social context it is introduced in. Whereas the more predictable rules of physics, chemistry or biology may have characterized the first phase of the evolution of an innovation, the next phase is defined by how individual incentives, social networks and market forces affect its propagation.

Early-adopters, with their preferences, needs, and attitude towards risk, influence not only how information about a new technology is acquired and broadcasted, but also adoption decisions by their peers and the institutions they are part of. Our results point to a novel, understudied mechanism through which early-adopters may influence technology adoption. Whereas the existing literature has often stressed their positive, network-effect building role, our results highlight a case where they might be obstructing further diffusion. While we cannot fully rule out that at least part of their behavior is due to their inability to help their peers learn about the technology when they are delayed, results are inconsistent with learning being the main explanation.

Early-adopters' decision to ignore the technology seems to be connected to their role as technology leaders and utility from exclusive access. By delaying them, we inadvertently either challenged their identity and reputation within their community, or substantially reduced the consumption utility they derive from early access. Because of the demographic involved in the study and setting (college students in dorms), effects are potentially amplified relative to what would be observed in the general population. At the same time, our findings are consistent with qualitative evidence coming from products that have been introduced into the market too early (essentially bypassing early-adopters) or by targeting customer segments that would not naturally gravitate towards the technology. One recent, high-profile example of this is the case of Google Glass [8], where Google,

[8] See http://www.nytimes.com/2015/02/05/style/why-google-glass-broke.html (accessed 01-28-2016).

under pressure from its marketing team to position the product as a fashion item, opened its beta product to journalists and fashion influencers well before the technology had been refined within the more forgiving community of developers. Similarly, crowdfunding projects have run into problems when the early-adopters who had funded them received the product after regular customers (i.e., when the waiting list was not honored).[9]

The experimental nature of our data, combined with fine-grained information about individual outcomes, allows us for the first time to cleanly estimate the causal effect of short delays (two weeks) on adoption. Small changes in the initial availability of a technology among different types of users have a lasting effect on its potential: when access to the innovation is potentially visible to individuals who are currently excluded, seeding the technology while ignoring early adopters' needs for distinctiveness is counterproductive.

[9]See http://www.theverge.com/2015/11/18/9758214/coolest-cooler-amazon-kickstater-shipping-production-delay (accessed 01-30-2016).

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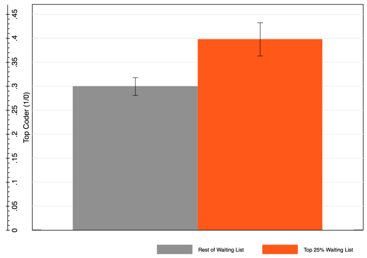
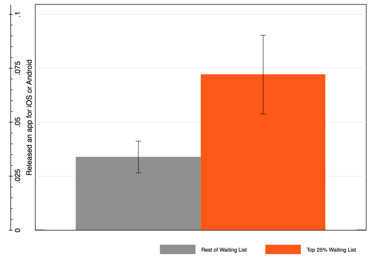
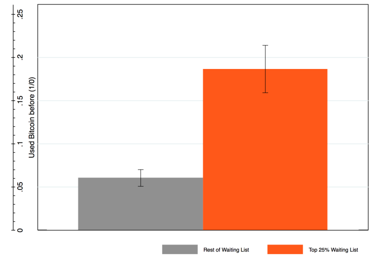
A Appendix



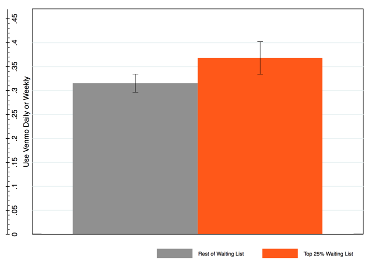
(a) Top Coder versus Not



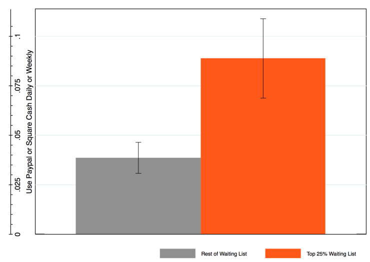
(b) Released iOS or Android App



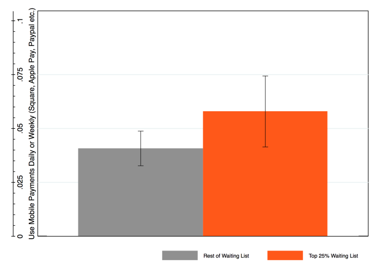
(c) Used Bitcoin Before



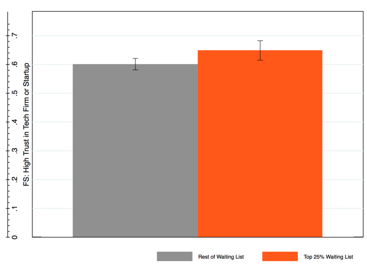
(d) Uses Venmo on a Daily or Weekly Basis



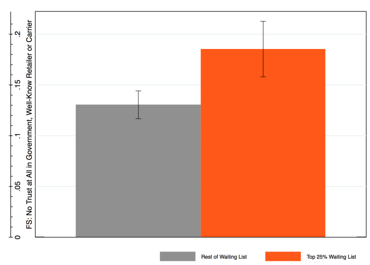
(e) Uses PayPal or SquareCash on a Daily or Weekly Basis



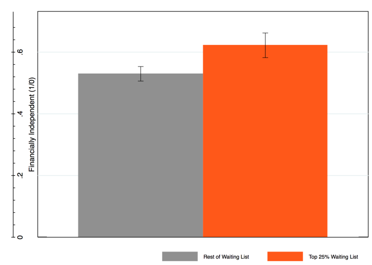
(f) Uses Mobile Payments on a Daily or Weekly Basis



(g) High Trust in Tech Firm or Startup for Financial Services



(h) No Trust at All in Government, Well-Known Retailer or Carrier for Financial Services



(i) Financial Independent versus Not

Figure A-1: Top 25% of the Waiting List and Early Adopter Traits

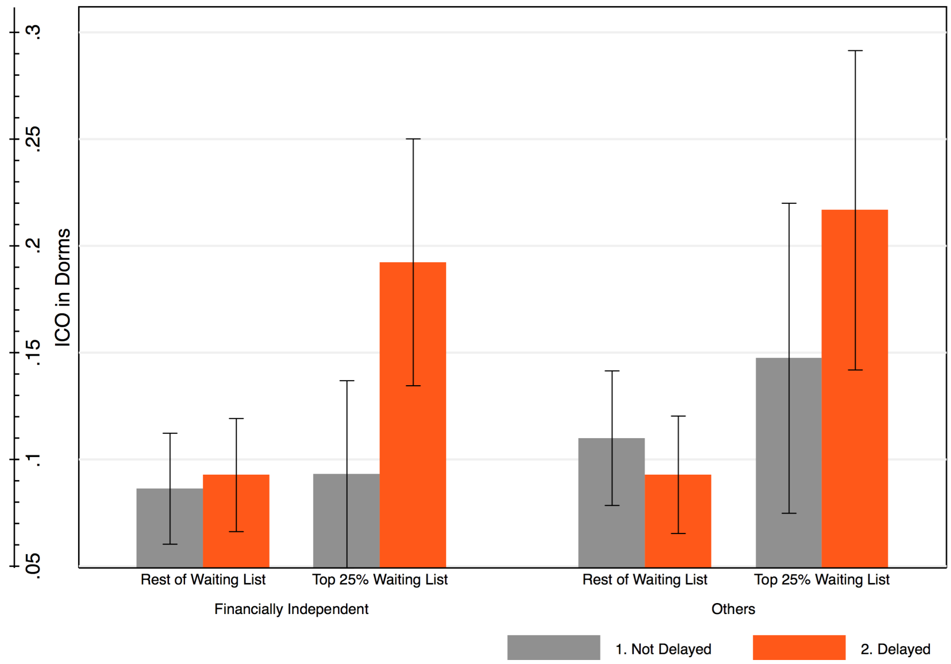


Figure A-2: Financially Independent versus Not

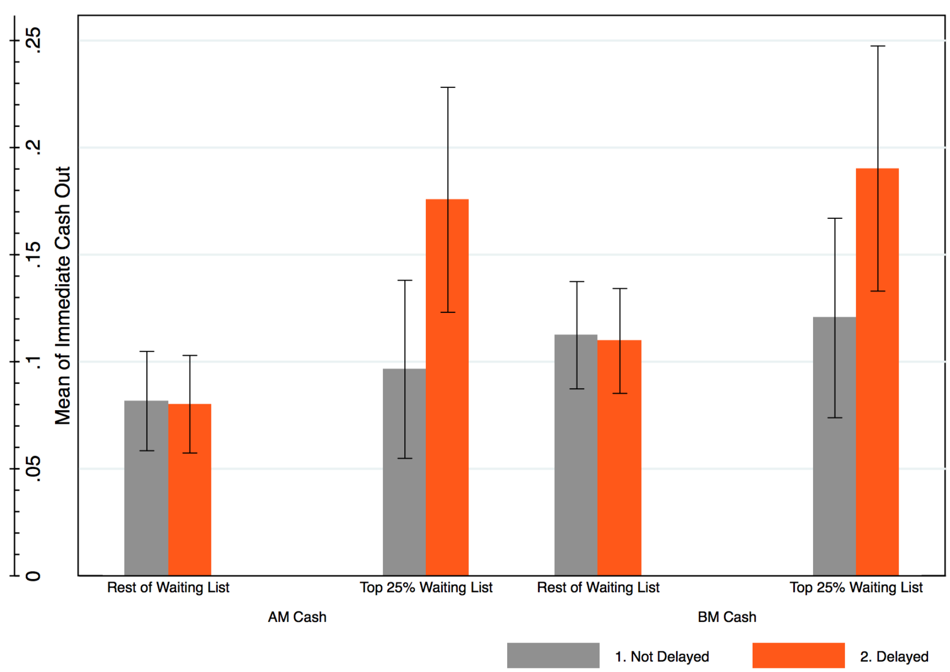
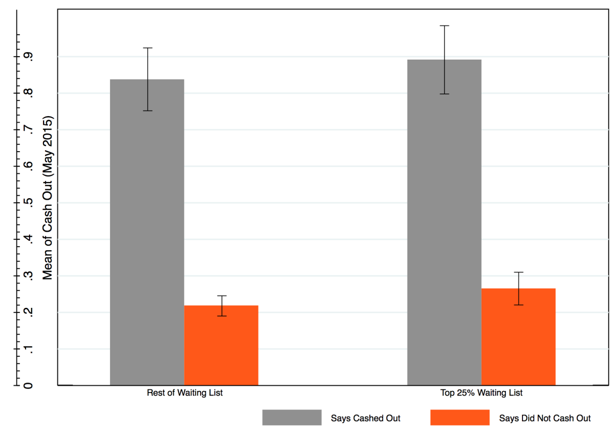
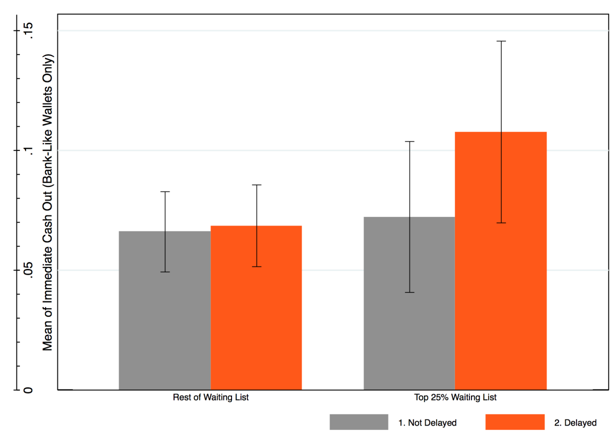


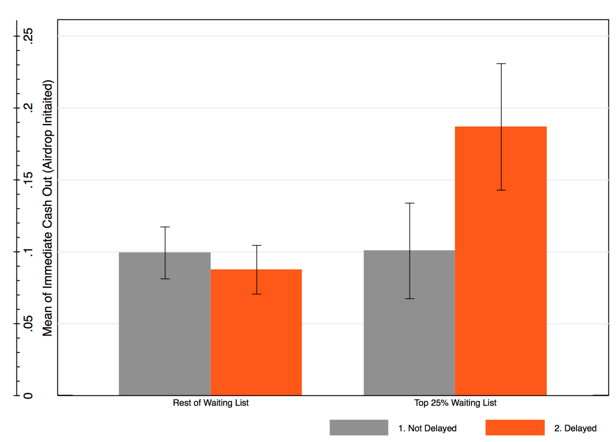
Figure A-3: Above versus Below Median Cash in Wallet



(a) Transaction Data versus Survey Measures



(b) Bank-Like Wallets Only



(c) Excluding Students Who Used Bitcoin Before

Figure A-4: Robustness of Abandonment Measure

Table A-1: Delaying Early-Adopters Increases Their Cash Out Rate. Effect is Coming From Dorms, Particularly Small Ones.

VARIABLES	(1) ICO	(2) ICO	(3) ICO	(4) ICO Off Campus	(5) ICO Dorms	(6) ICO Dorms Above Median Size	(7) ICO Dorms Below Median Size
Top 25% Waiting List	1.5851***	1.6864***	1.0427	1.2379	1.0601	1.1329	1.0561
	(0.1958)	(0.2209)	(0.2045)	(0.4517)	(0.2504)	(0.3089)	(0.5253)
Delayed			0.9236	1.3518	0.9774	1.0993	0.7211
			(0.1758)	(0.4972)	(0.2096)	(0.2693)	(0.3268)
Top 25% Waiting List * Delayed			1.9113**	1.0267	2.0920**	1.6352	4.1052**
			(0.4986)	(0.5439)	(0.6342)	(0.5731)	(2.6105)
All Delayed			0.9772	0.7125	0.9442	0.9138	1.0209
			(0.1712)	(0.2595)	(0.1849)	(0.2065)	(0.4167)
Privacy Text		0.7554**	0.7286***	0.7328	0.7186**	0.6961**	0.7543
		(0.0899)	(0.0886)	(0.1757)	(0.1020)	(0.1161)	(0.2145)
Wallet Matrix		0.8676	1.1041	0.8710	1.1889	1.2001	1.2540
		(0.1028)	(0.1361)	(0.2105)	(0.1723)	(0.1985)	(0.3840)
Public Directory		0.6889**	0.7117**	0.4161***	0.8108	0.6685*	1.2883
		(0.1028)	(0.1070)	(0.1412)	(0.1376)	(0.1382)	(0.4059)
LibertyX		9.9149***	4.8736***	9.6768***	4.0400***	4.4420***	3.1093**
		(2.4674)	(1.2462)	(5.5882)	(1.1440)	(1.6089)	(1.5163)
Expected Price Decay		1.7957***	1.8580***	1.4371	2.1311***	2.3848***	1.3229
		(0.2506)	(0.2646)	(0.4579)	(0.3402)	(0.4454)	(0.4173)
New To Bitcoin		0.7458*	0.7422	1.1382	0.6349**	0.7022	0.4456*
		(0.1287)	(0.1368)	(0.4123)	(0.1364)	(0.1765)	(0.1975)
East Dorms		1.7279***					
		(0.2554)					
West Dorms			0.6235***				
			(0.1012)				
Off Campus			0.6634**				
			(0.1229)				
CS Student			0.7760*	0.9122	0.7159*	0.6580**	0.9175
			(0.1014)	(0.2630)	(0.1267)	(0.1387)	(0.3007)
Circle			0.1321***	0.2378***	0.1102***	0.1130***	0.1046***
			(0.0311)	(0.1193)	(0.0299)	(0.0354)	(0.0567)
Coinbase			0.5107***	1.6929*	0.3439***	0.3537***	0.3236***
			(0.0715)	(0.4895)	(0.0567)	(0.0675)	(0.1077)
Top Coder				0.9606	1.1177	1.1887	0.8683
				(0.2669)	(0.1994)	(0.2467)	(0.3098)
Constant	0.0677***	0.0768***	0.4293***	0.1144***	0.3625***	0.3139***	0.5765
	(0.0117)	(0.0210)	(0.1185)	(0.0565)	(0.1032)	(0.1062)	(0.3153)
Observations	3,108	3,108	3,108	810	2,298	1,766	532

Robust Std. Errors in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-2: Above and Below the Median Density of Early Bitcoin Users, Tech Talent and Early Adopters in Dorms

VARIABLES	(1) ICO in Dorms Top Coders	(2) ICO in Dorms Other Students	(3) ICO in Dorms BM BTC Adopters	(4) ICO in Dorms AM BTC Adopters	(5) ICO in Dorms BM CS Students	(6) ICO in Dorms AM CS Students	(7) ICO in Dorms BM Early Adopters	(8) ICO in Dorms AM Early Adopters
Top 25% Waiting List	0.8238	1.1974	0.8191	1.2981	1.3696	0.9343	0.3317	1.2519
	(0.3141)	(0.3587)	(0.3241)	(0.4043)	(0.4434)	(0.3280)	(0.2479)	(0.3581)
Delayed	0.4522**	1.4340	0.6962	1.3197	0.8465	1.1274	0.9237	1.0058
	(0.1828)	(0.3677)	(0.2542)	(0.3639)	(0.2755)	(0.3321)	(0.3153)	(0.2966)
Top 25% Waiting List	3.7971**	1.6398	4.4449***	1.1698	3.2689***	1.1729	8.8761***	1.6336
* Delayed	(1.9889)	(0.6247)	(2.1749)	(0.4656)	(1.3970)	(0.5267)	(7.4363)	(0.6048)
All Delayed	1.1361	0.8202	0.9436	0.9726	0.8032	1.0222	0.9393	0.9957
	(0.4049)	(0.1936)	(0.3132)	(0.2539)	(0.2312)	(0.2830)	(0.3291)	(0.2419)
Privacy Text	0.9538	0.6157***	0.9024	0.5955***	0.8109	0.6606**	0.5897**	0.7977
	(0.2336)	(0.1090)	(0.1920)	(0.1161)	(0.1668)	(0.1348)	(0.1365)	(0.1483)
Wallet Matrix	1.1866	1.1744	1.0770	1.3126	1.3852	1.0043	1.0087	1.2620
	(0.3010)	(0.2084)	(0.2410)	(0.2542)	(0.2800)	(0.2116)	(0.2381)	(0.2319)
Public Directory	0.8615	0.8034	0.8323	0.8088	0.7048	0.9205	0.8461	0.7636
	(0.2528)	(0.1696)	(0.2093)	(0.1898)	(0.1850)	(0.2092)	(0.2269)	(0.1736)
LibertyX	3.4013**	4.1262***	4.7283***	3.8124***	8.8509***	2.2030*	5.9230***	3.2899***
	(1.8527)	(1.3877)	(1.8516)	(1.6077)	(3.7365)	(0.9635)	(2.3961)	(1.3166)
Expected Price Decay	2.8393***	1.8891***	1.6998**	2.5455***	1.3024	3.0147***	1.9787***	2.2813***
	(0.7684)	(0.3792)	(0.4593)	(0.5286)	(0.3217)	(0.6424)	(0.5116)	(0.4779)
New To Bitcoin	0.5162**	0.7582	0.6172	0.6053**	0.6443	0.5954*	0.8982	0.5214**
	(0.1689)	(0.2290)	(0.4112)	(0.1469)	(0.2144)	(0.1724)	(0.3686)	(0.1379)
CS Student	0.7562	0.6677*	0.6369	0.7885	0.8709	0.7887	0.6340	0.7549
	(0.2096)	(0.1603)	(0.1757)	(0.1839)	(0.2461)	(0.1841)	(0.1888)	(0.1690)
Circle	0.1909***	0.0800***	0.1304***	0.0993***	0.1109***	0.1160***	0.1410***	0.1025***
	(0.0811)	(0.0286)	(0.0514)	(0.0378)	(0.0463)	(0.0418)	(0.0601)	(0.0366)
Coinbase	0.3004***	0.3584***	0.4000***	0.2997***	0.4886***	0.2650***	0.6443*	0.2355***
	(0.0921)	(0.0702)	(0.1003)	(0.0663)	(0.1124)	(0.0631)	(0.1704)	(0.0520)
Top Coder			0.8214	1.4421	1.3637	1.0597	0.9532	1.2264
			(0.2288)	(0.3401)	(0.3598)	(0.2488)	(0.2945)	(0.2753)
Constant	0.4994	0.3001***	0.4438	0.2969***	0.2923***	0.3785**	0.2557***	0.4294**
	(0.2362)	(0.1143)	(0.3279)	(0.1085)	(0.1250)	(0.1518)	(0.1190)	(0.1685)
Observations	697	1,601	1,018	1,280	993	1,305	1,021	1,277

Robust Std. Errors in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

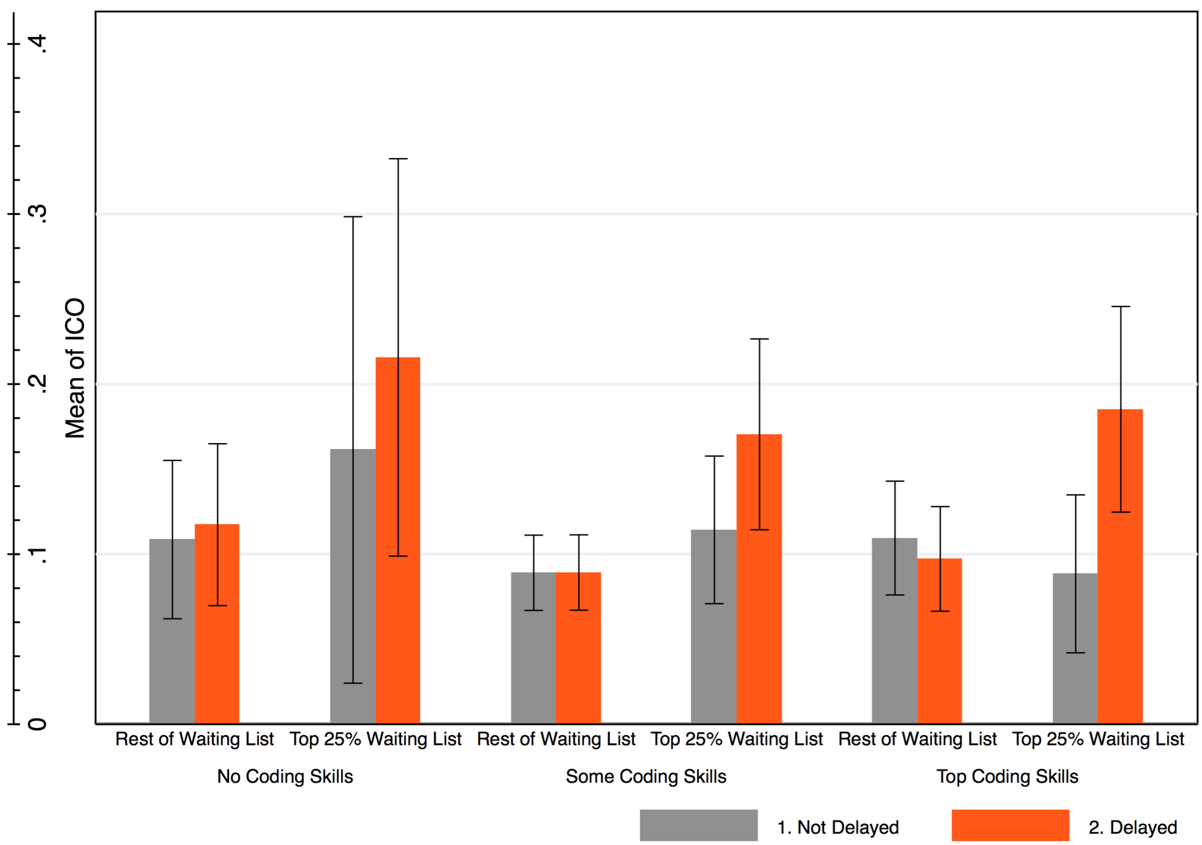


Figure A-5: Tech Skills

Table A-3: Tech Skills

VARIABLES	(1) ICO in Dorms No Coding Skills	(2) ICO in Dorms Some Coding Skills	(3) ICO in Dorms Top Coding Skills	(4) ICO in Dorms
Top 25% Waiting List	2.6582*	0.9462	0.8238	2.3898
	(1.5314)	(0.3341)	(0.3141)	(1.4197)
Delayed	1.1910	1.4718	0.4522**	1.5122
	(0.6756)	(0.4317)	(0.1828)	(0.6316)
Top 25% Waiting List * Delayed	0.8558	2.0178	3.7971**	0.7652
	(0.6630)	(0.8997)	(1.9889)	(0.5836)
Some Coding Skills				0.8016
				(0.2729)
Top Coding Skills				1.4533
				(0.5457)
Top 25% Waiting List * Some Coding Skills				0.4246
				(0.2915)
Top 25% Waiting List * Top Coding Skills				0.3546
				(0.2511)
Delayed * Some Coding Skills				0.8531
				(0.3961)
Delayed * Top Coding Skills				0.3367**
				(0.1777)
Top 25% Waiting List * Delayed * Some Coding Skills				2.5204
				(2.2158)
Top 25% Waiting List * Delayed * Top Coding Skills				4.9685*
				(4.6125)
All Delayed	1.2425	0.7064	1.1361	0.9033
	(0.6625)	(0.1914)	(0.4049)	(0.1778)
Privacy Text	0.5223*	0.6324**	0.9538	0.7023**
	(0.1930)	(0.1327)	(0.2336)	(0.1013)
Wallet Matrix	1.9946*	0.9521	1.1866	1.1612
	(0.7061)	(0.2061)	(0.3010)	(0.1691)
Public Committment	0.4824	0.9685	0.8615	0.8152
	(0.2414)	(0.2286)	(0.2528)	(0.1394)
LibertyX	13.0072***	2.6763**	3.4013**	3.8772***
	(9.3148)	(1.0774)	(1.8527)	(1.0940)
Expected Price Decay	1.7438	1.9847***	2.8393***	2.2257***
	(0.8764)	(0.4519)	(0.7684)	(0.3575)
New to Bitcoin	0.8208	0.7027	0.5162**	0.6397**
	(0.4769)	(0.2510)	(0.1689)	(0.1392)
CS Student	0.4961	0.7216	0.7562	0.7276*
	(0.4436)	(0.1808)	(0.2096)	(0.1318)
Circle	0.1163***	0.0718***	0.1909***	0.1084***
	(0.0782)	(0.0307)	(0.0811)	(0.0294)
Coinbase	0.7732	0.2751***	0.3004***	0.3398***
	(0.3054)	(0.0652)	(0.0921)	(0.0562)
Constant	0.1754**	0.3638**	0.4994	0.3733***
	(0.1366)	(0.1618)	(0.2362)	(0.1411)
Observations	359	1,242	697	2,298

Robust std errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-4: All Delayed versus None Delayed

VARIABLES	(1) ICO in Dorms - None Delayed	(2) ICO in Dorms - All Delayed
Top 25% of Waiting List	1.0094	2.5693***
	(0.2784)	(0.6955)
Privacy Text	0.7634	0.7013
	(0.1871)	(0.1818)
Wallet Matrix	1.0029	1.3699
	(0.2594)	(0.3577)
Public Commitment	0.4414**	1.1923
	(0.1463)	(0.3440)
LibertyX	12.5168***	2.9087**
	(6.2837)	(1.4509)
Expected Price Decay	1.8621**	2.7948***
	(0.5232)	(0.7919)
New to Bitcoin	0.6942	0.3976**
	(0.2562)	(0.1628)
CS Student	0.4597**	0.7920
	(0.1553)	(0.2456)
Circle	0.1904***	0.0780***
	(0.0808)	(0.0395)
Coinbase	0.4526***	0.2724***
	(0.1322)	(0.0824)
Top Coder	2.4898***	0.8257
	(0.8246)	(0.2683)
Constant	0.2653**	0.1800**
	(0.1572)	(0.1219)
Observations	931	721

Robust std. errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

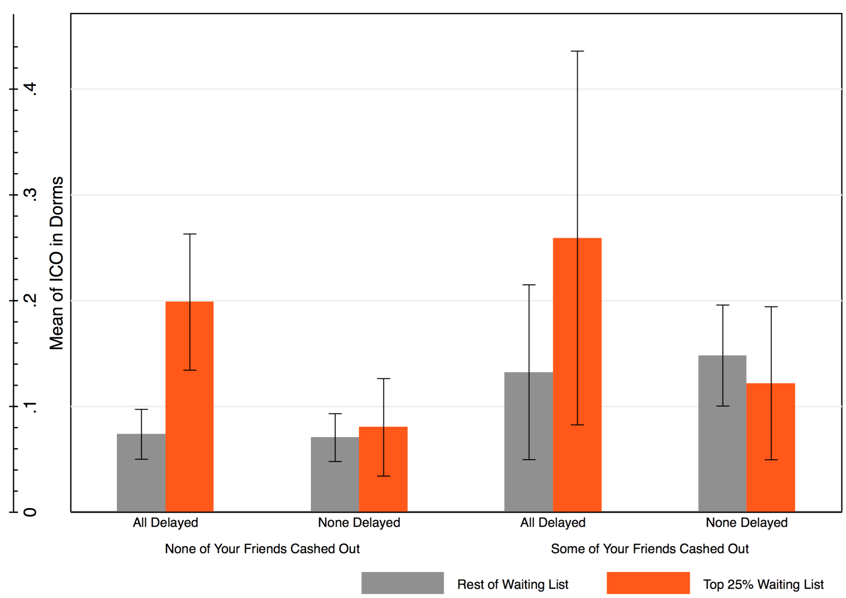


Figure A-6: All Delayed versus None Delayed and Cash Out by Friends

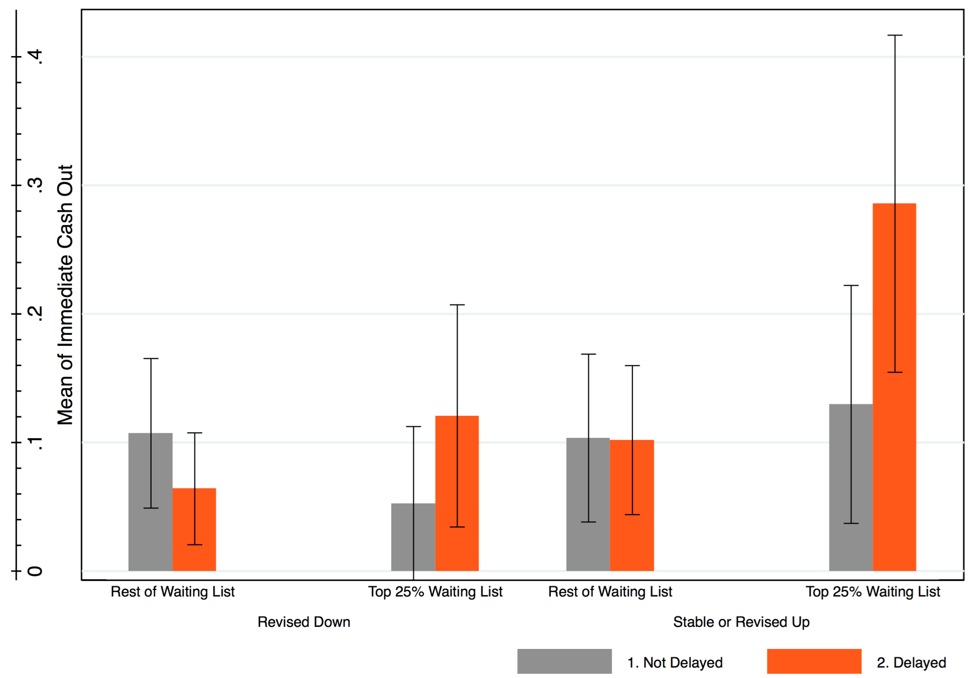
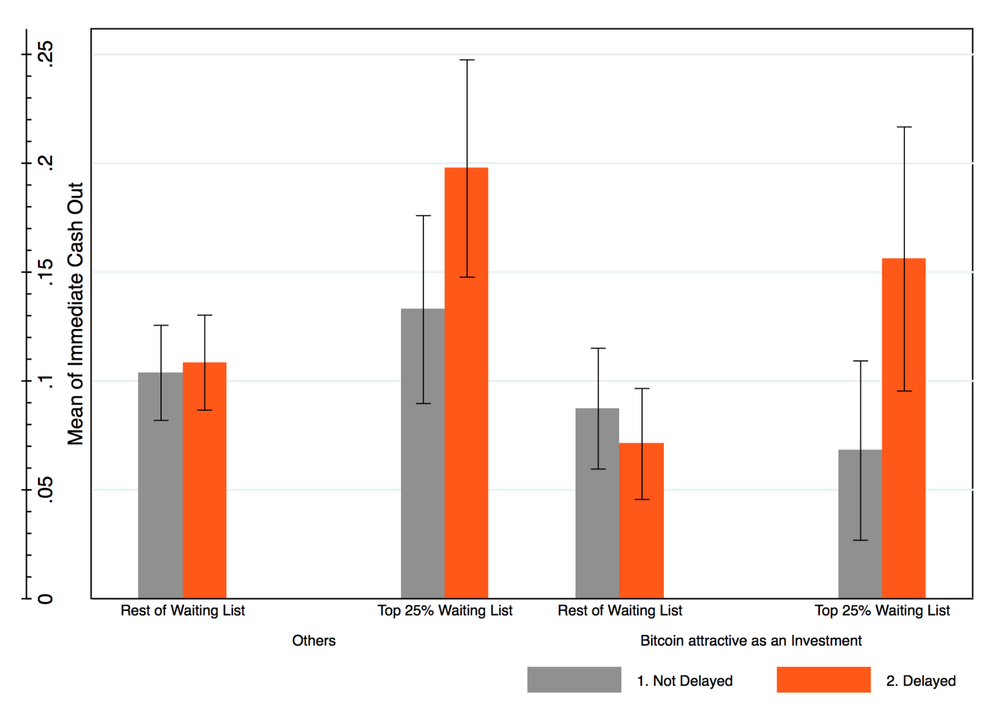
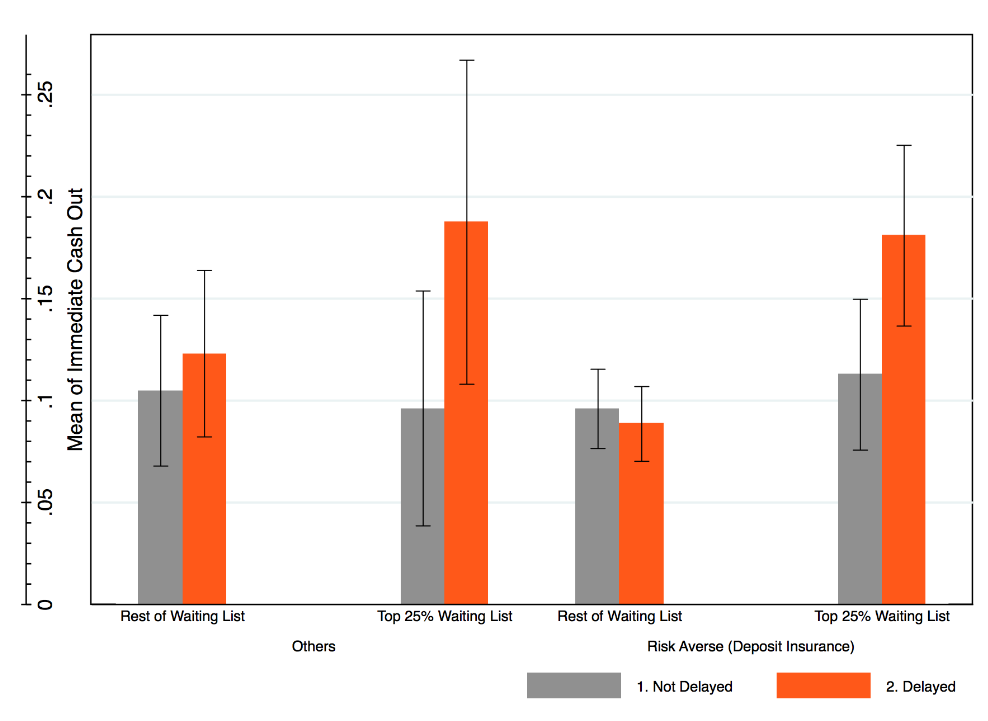


Figure A-7: Change in Expectations About the Price of Bitcoin

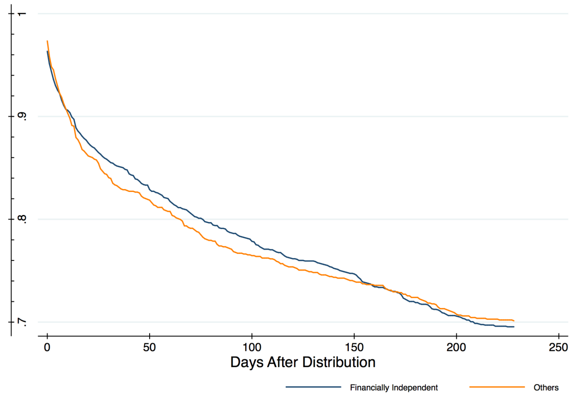


(a) Bitcoin Attractive as an Investment Vehicle vs Not

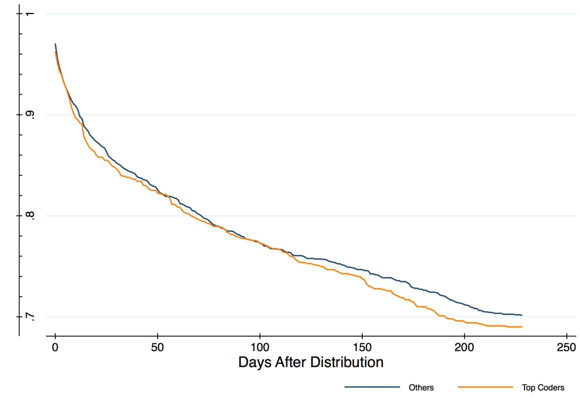


(b) Risk Aversion

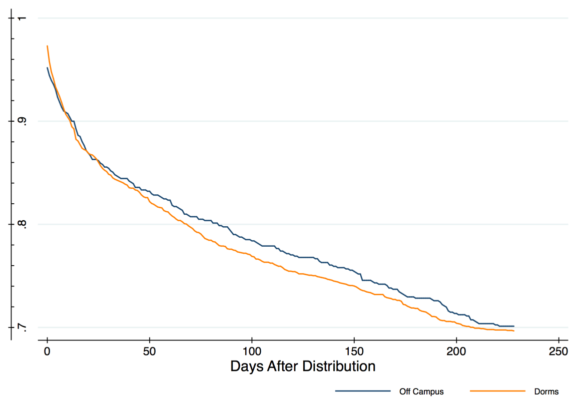
Figure A-8: Bitcoin as an Investment and Risk Aversion



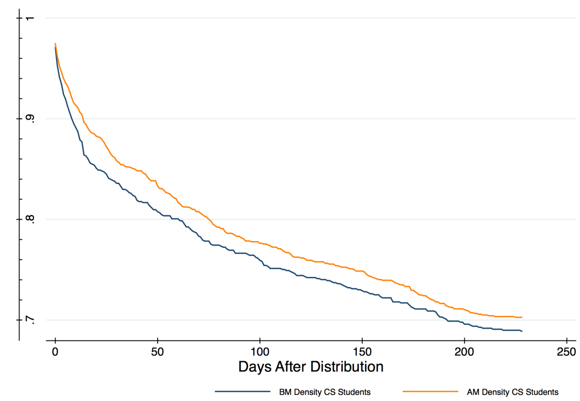
(a) By Financially Independent versus Not



(b) By Top Coders versus Not



(c) By Dorms versus Off Campus



(d) By Above the Median versus Below the Median Density of Computer Science Students

Figure A-9: Additional Abandonment Curves

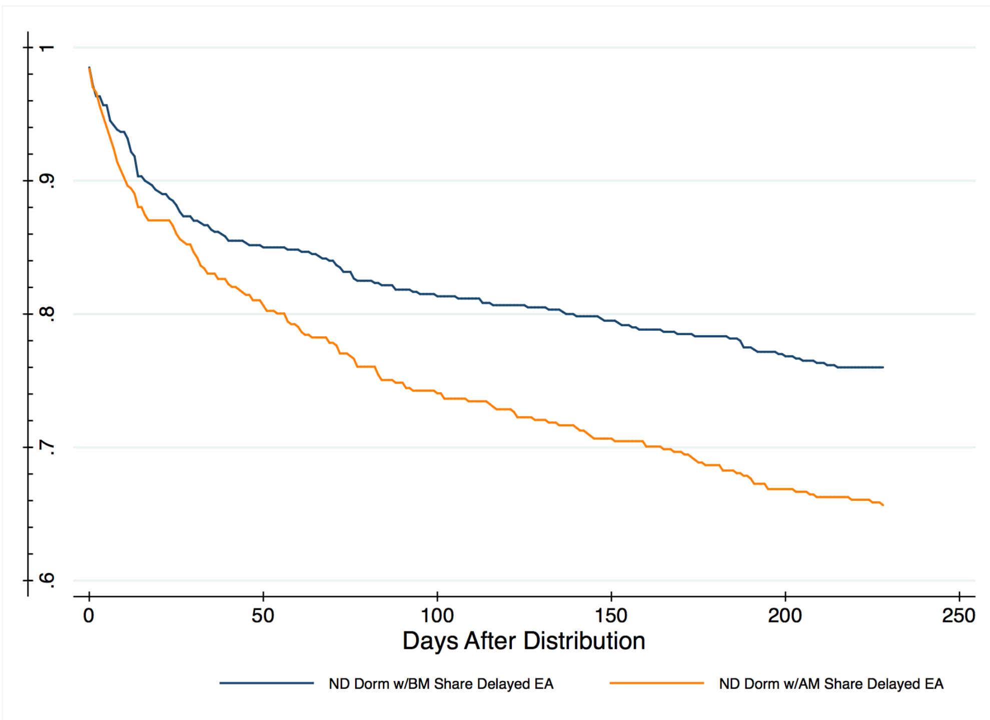


Figure A-10: Spillover Effects Within Dorms (Excluding All Delayed Students)