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

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Abstract

In October 2014, all 4,494 undergraduates at the Massachusetts Institute of Technology were given access to Bitcoin, a decentralized digital currency. As a unique feature of the experiment, students who would generally adopt first were placed in a situation where many of their peers received access to the technology before them, and they then had to decide whether to continue to invest in this digital currency or exit. Our results suggest that when natural early adopters are delayed relative to their peers, they are more likely to reject the technology. We present further evidence that this appears to be driven by identity, in that the effect occurs in situations where natural early adopters' delay relative to others is most visible, and in settings where the natural early adopters would have been somewhat unique in their tech-savvy status. We then show not only that natural early adopters are more likely to reject the technology if they are delayed, but that this rejection generates spillovers on adoption by their peers who are not natural early adopters. This suggests that small changes in the initial availability of a technology have a lasting effect on its potential: Seeding a technology while ignoring early adopters' needs for distinctiveness is counterproductive.

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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 ever 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 et al., 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 were very limited, making it an ideal context for studying the early stages of technology adoption.[1]

A unique feature of our research design was that it attempted to accelerate the early stages of technology diffusion by randomizing the order in which students received their Bitcoin: Some early adopters had to wait for two additional weeks, whereas some natural late adopters were placed in the unfamiliar situation of being among the first to hold the digital currency. All students had to decide whether to hold onto this new type of digital currency 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 students who were either natural early adopters or not, affected whether or not they rejected the technology. The technology was exogenously introduced and everyone was temporarily turned into a user, because in order to participate, students had to create and secure their own digital wallet. Consequently, we focus on the students' decision to revert our intervention, that is to reject Bitcoin and exchange it for US dollars.

[1] The price of Bitcoin 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. Bitcoin's extremely high volatility was a clear reflection of its experimental nature and of how even insiders had a difficult time assessing its value, whether it would diffuse further, disappear, or eventually be replaced by a better implementation of the same cryptographic ideas (Böhme et al., 2015; Gandal and Halaburda, 2016).

We identify early adopters by their eagerness in signing up for the waitlist for Bitcoin. We also provide reassuring evidence that this eagerness is correlated with other characteristics associated with being an early adopter and not other characteristics that could provide alternative explanations for our findings.

We find that if natural adopters are randomly delayed, they are more likely to reject the technology rather than attempting to use it. After testing the robustness of our results to a battery of alternative explanations, such as price expectations and financial neediness, we explore what drove this behavior. We found that natural early adopters rejecting Bitcoin is most likely to occur in situations where the delayed natural early adopter is more likely to observe others who are not natural early adopters adopt the technology first, such as in a close-knit dorm environment. By contrast, if a natural early adopter lived outside of campus there was little effect. We also observe that it is more likely to occur when the natural early adopter is somewhat socially unique rather than common.

We then turn to see whether this rejection of the technology by natural early adopters had spillovers for their peers. We find that dorms and social clusters where an above-the-median share of early adopters were delayed, were characterized by more students subsequently rejecting the currency. This is consistent with intentional exit by delayed early adopters having negative spillovers on the ultimate usage of the technology by others close to them.

While the existing literature has stressed the positive, network-effect building role of individuals who seek early adopter status, our results 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 and potentially tying their identity to being first to adopt technologies, excluding them from early access has a strong effect on the likelihood that they will reject the technology.

Our paper contributes to three related streams of research.

The first literature we contribute to is the literature on technology diffusion (Griliches, 1957; Rogers, 1962; Bass, 1969; Jensen, 1982; Mansfield and Mansfield, 1993). This literature emphasises the role early adopters play in defining the success of a new innovation, early feedback for the innovation (Von Hippel, 1978, 1986, 2005), and the speed at which it diffuses (Mahajan et al., 1990). Early adopters are typically individuals who receive higher initial benefit from adoption, either because of their idiosyncratic preferences or because of how the technology improves 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. A key challenge for empirical research in this area is that in the absence of exogenous variation, we never observe a counterfactual diffusion curve in observational data. This is particularly problematic because the segment of users that is targeted first endogenously defines the shape and evolution of an S-curve (Aral and Walker, 2012; Gans et al., 2016): By choosing a particular customer segment, firms are indirectly determining the speed at which their product or service will diffuse. As such, sequential rollout affects the ultimate speed of diffusion (Chintagunta et al., 2010). Our paper suggests that one of the conditions for early adopters to successfully propel a technology is that they are uniquely early. In other words, it is impossible to enjoy the benefits of the early adopter community without ensuring that they occupy their distinct early place on the diffusion-curve.

The second literature we contribute to is the literature on observational learning and peer effects. Early adopters can influence their peers through rational, observational learning (Banerjee, 1992; Vives, 1993; Glaeser et al., 1996; Bikhchandani et al., 1998; Zhang, 2010; Tucker and Zhang, 2011) or through social influence (Katz and Lazarsfeld, 1955; Fisher and Price, 1992; Watts and Dodds, 2007; Iyengar et al., 2011). Our paper suggests that for these peer effects to take place, early adopters need others to have not adopted the technology.

The third literature we contribute to is the literature on identity, fashion leaders and trend cycles which emphasizes the need to balance a potential early adopter's need for conformity versus differentiation (Brewer, 1991; Berger and Heath, 2007; Leonardelli et al., 2010; Chan et al., 2012; Sun et al., 2012; Zuckerman, 2015), and the heterogeneous role intangibles may play in the utility function of different types of users (Pesendorfer, 1995; Zhang and Zhu, 2011; Gautam et al., 2016). We show that some of the insights on trend cycles can also potentially apply to diffusion curves. Seeding a new technology while ignoring the need 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.

Our paper also has managerial implications. Many firms strategically manage the availability of a new product and rely on a waitlist to identify early adopters: individuals that are more eager to try a new product sign up first, or line up for hours in front of a store on the day of a product release, revealing in the process their early-adopter nature. A successful example of a waitlist approach is Google's in the rollout of Gmail: the company decided to seed adoption by offering Gmail to a few thousand initial users, who would then be able to select the next batch of users through personal invites. The social nature of the process, combined with the exclusivity coming from the limited capacity and invitation waves, transformed Gmail into a sought-after 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 such as Kickstarter and Indiegogo have institutionalized the seeding process by capitalizing on early adopters' higher willingness to pay for early access to directly fund the development of early-stage projects (Agrawal et al., 2013). Our results, suggest that not only may there be logistical or financial reasons for not having a overly comprehensive launch, but also that by restricting the reach of a product launch, managers can fulfill early adopters' need to be unique.

2 Empirical Setting and Data

The background to the setting we study is an experiment launched by the MIT Bitcoin Club to give every undergraduate at MIT $100 in bitcoin. Though the focus of this paper is not cryptocurrencies or associated Blockchain technologies, it is worth summarizing the logistics of the distribution. In 2014, members of the MIT Bitcoin Club raised sufficient money from MIT Alumni to give each of 4,494 MIT undergraduates $100 in bitcoin. Students then signed up to a waitlist to receive their bitcoin, during which process they answered a variety of survey questions about themselves and their use of technology and also signed up for a 'digital wallet' that would allow them to receive their bitcoin. They had five days to sign up to this waitlist. 3,108 undergraduates, around 70%, signed up for a digital wallet. A few weeks later bitcoin began to be distributed to the undergraduate population who had signed up for a digital wallet.

To answer our research question - which is how is the spread of technology affected when natural early adopters are either delayed or not - we need three things. First, we need the ability to perturb the natural order of adoption and generate exogenous variation in the adoption sequence. Second, we need a way to separate early adopters from other users before the technology; and third, we need data on technology (dis)adoption by individuals over time.

We perturb the natural order of adoption by relying on the random assignment of students to one of two distribution cohorts. 50% of participants were randomly delayed in receiving their bitcoin relative to their peers by two weeks. No mention had been made in the initial sign up process about the timing of the distribution of bitcoin - they were just informed loosely that they would receive it soon. Neither was any explanation given at the time of the first distribution 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. A key advantage this randomization gives us over observational data is that it allows us in Section 3.5 to estimate 'counterfactual' diffusion curves by directly comparing disadoption across groups of students that received different degrees of exposure to the delay.

We use the order in which students signed up for the bitcoin distribution and to be on the waitlist to distinguish those who would naturally seek early adopter status versus not. The first 777 students that registered with us, who were the first 25% of our sample, are classified as early adopters.[2] The process was analogous to how startups or technology firms such as Google progressively deliver access to new users when faced with capacity constraints by using a waitlist that potential users can sign up with and then by allowing access on the basis of how early a user signed up, or to distributing a product first to the people who lined up earliest at a store on the day of a product launch.

We focus on disadoption or rejection of the technology simply because the nature of the experiment was that all users were forced to 'adopt' the technology as they were given $100 in bitcoin. Specifically, we use as our dependent variable to proxy disadoption whether students cashed out their bitcoin within two weeks from receiving them, or decided to keep them for longer. To track cashing out, we obtain transaction data directly from digital wallet providers and, for participants who do not use an intermediary because they selected an open-source digital wallet like Electrum, from the Bitcoin blockchain. The Bitcoin blockchain is the public, digital ledger that records every transaction between Bitcoin users. We also check the robustness of our results to a battery of alternative measures of exit or disadoption.

We complement transaction data with survey information coming from our registration process, as well as survey data that covers social network data where the student gave contact details for five of their friends, attitude towards Bitcoin and other financial technology, spending patterns and preferences. Demographic information is provided by the Institutional Research section of the MIT Office of the Provost. Relative to the overall MIT population,

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

our sample is slightly more likely to be male, a US citizen, to be majoring in Electrical Engineering and Computer Science, and to be enrolled in the first three years of the program.

Table 1 presents descriptive statistics for our main sample: 3,108 undergraduate students participated in the study, with 50% of the sample receiving their bitcoin in early November, and the remaining 50% receiving them exactly two weeks later ("Delayed"). 11% of students cashed out their bitcoin within two weeks from receiving them ("Cash Out").[3]

74% of participants live in dorms, with the majority residing in "West Dorms" on the west side of Massachusetts Avenue in Cambridge. During the sign-up process, 71% of students selected a bank-like digital wallet hosted by a financial intermediary over open-source alternatives. Students were generally optimistic about the future exchange price of Bitcoin to US dollars: Only 17% believed the currency would decrease in value within the next 6 months. The vast majority, specifically 89%, were new to Bitcoin, and were interested in the digital currency as a potential investment (35%), as an alternative to cash (21%) and for online transactions (20%). 36% of our sample were computer science students.

We also used this descriptive data to verify that indeed the top 25% of the waitlist did exhibit the classic characteristics of early adopters. Figures 1a through 1d present survey data that we collected from students which corroborate our "revealed preferences" approach to identifying early adopters: The first students on the waitlist are more likely to be top coders, or to have developed their own mobile application, to use new payments apps like Square Cash, and to place more trust than their peers in tech firms and startups for their financial services, though this last difference is not significant.

[3]In another paper, we explore two additional randomizations connected with surveillance which were an encryption prompt ("Encryption Randomization", displayed to 50% of our sample) and a nudge highlighting the potential for government surveillance ("Surveillance Nudge Randomization"), and their effects on attitudes towards data-usage among students. In future work, we also hope to study the long-run effects of a simple nudge to incentivize students to include their Bitcoin wallet address in a public directory ("Public Commitment Randomization", displayed to 25% of our sample). In this paper we merely control for these randomizations.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Cash Out	0.111	0.314	0	1	3,108
Top 25% of the Waiting List	0.25	0.433	0	1	3,108
Randomizations					
Delayed by 2 Weeks	0.504	0.5	0	1	3,108
Encryption Rand.	0.507	0.5	0	1	3,108
Surveillance Nudge Rand.	0.504	0.5	0	1	3,108
Public Commitment Rand.	0.254	0.435	0	1	3,108
Location					
Dorm	0.739	0.439	0	1	3,108
Wallet Type and Student Characteristics					
Bank-Like Wallet	0.713	0.452	0	1	3,108
Expected Price Decay	0.171	0.377	0	1	3,108
New to Bitcoin	0.886	0.317	0	1	3,108
Computer Science Student	0.358	0.479	0	1	3,108

3 Results

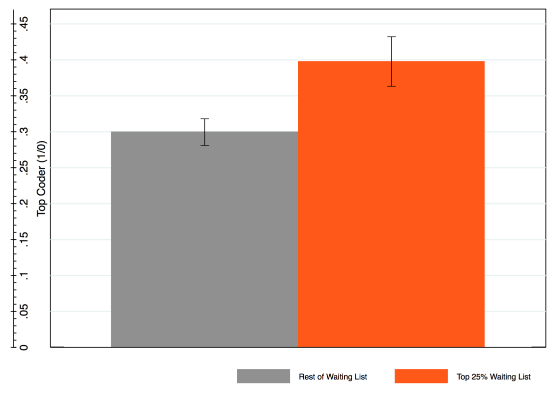
3.1 Model-Free Evidence

Figure 2 presents the main result of the paper. Most students are indifferent to receiving their bitcoin early or after two weeks. We observe a 9.8% cash out rate within two weeks when not delayed, and 9.6% when delayed (p=0.8653). However, 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).

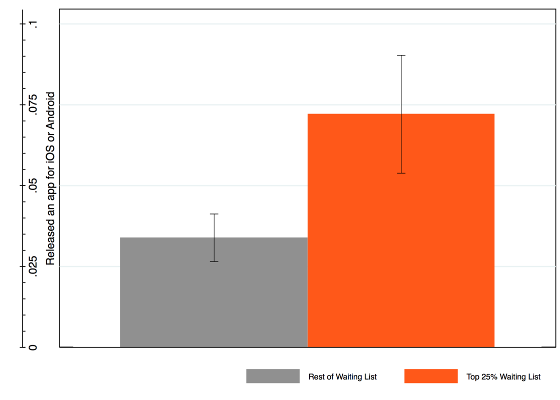
3.2 Regression Approach

Even though we essentially rely on randomized variation for part of our main effect, to investigate the robustness of our results to a variety of controls we turn to a regression format. Reassuringly, our results are the same when we add additional controls.

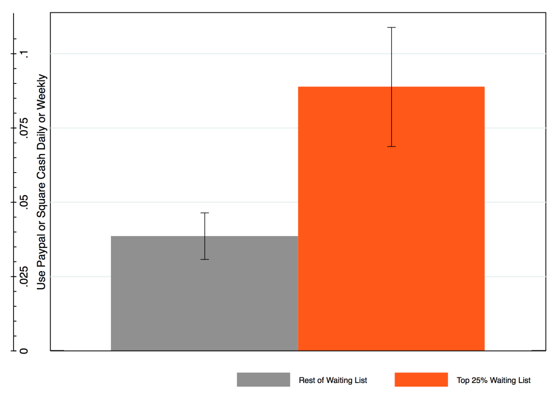
Our econometric analysis uses cross-sectional logit regressions, such that for student i we relate whether or not they disadopted the technology in the following manner:



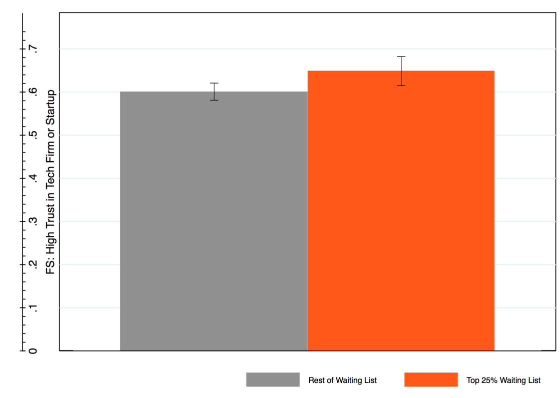
(a) Top Coder versus Not



(b) Released iOS or Android App



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



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

Figure 1: Top 25% of the WaitList and Early Adopter Traits

$$CashOut_i = \beta_1 EarlyAdopter_i + \beta_2 Delayed_i + \beta_3 EarlyAdopter \times Delayed_i + X_i + R_i + \epsilon_i \quad (1)$$

Where $CashOut_i$ is a binary indicator for cashing out within two weeks from receiving bitcoin, $EarlyAdopter_i$ is a binary indicator equal to one if the student is classified as an early-adopter according to our waitlist, $Delayed_i$ is a dummy equal to one if the student was randomly delayed by two weeks, and $EarlyAdopter \times Delayed_i$ is an interaction of the other two terms. X_i is a vector of student characteristics such as dorm, software development skills, digital wallet used and expectations about future Bitcoin price; R_i is a vector of controls for

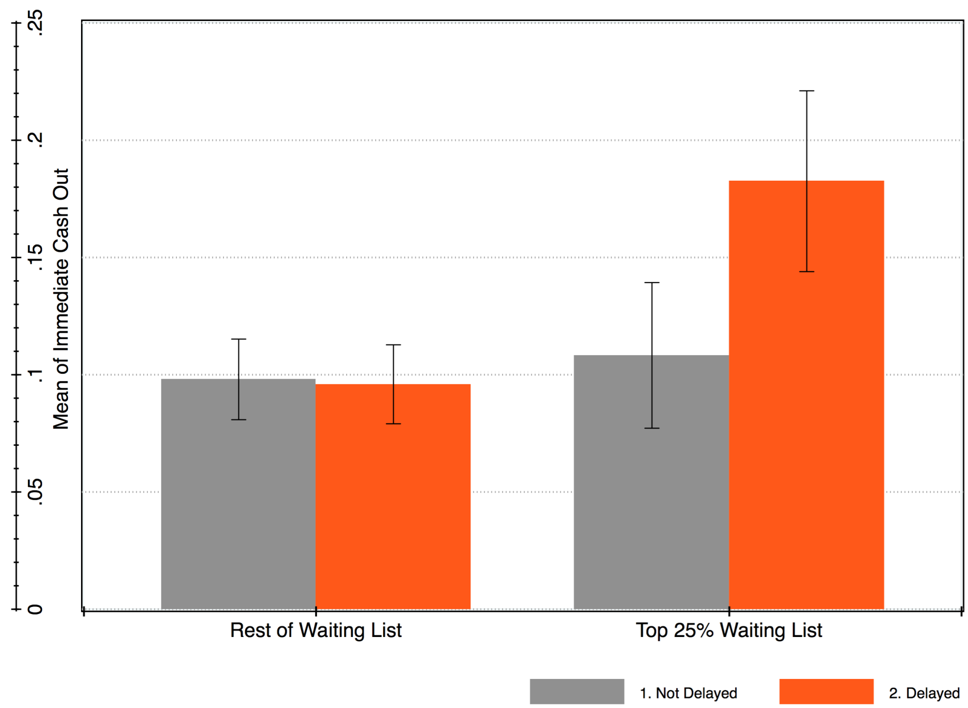


Figure 2: Delaying Early Adopters Increases Their Cash Out Rate

other randomizations the focal participant was part of. ϵ_i is an idiosyncratic error term. In all cases we report robust standard errors.

In Table 2 each column reports odds-ratios for our initial logit specification. The base specification reported in Column (2) suggests that delayed early adopters are 1.87 times more likely to cash out than non-delayed, regular users. Our results do not change when we add controls for the type of wallet adopted by the students in Column (3), their location on campus in Column (4), add controls for additional student characteristics in Column (5), and other randomizations in Column (6). In fact, these additional controls slightly increase the magnitude of the effect to 1.97 times the baseline and reduce our standard errors around the estimate. The other coefficients in Table 2 are generally consistent with what one would expect: Not surprisingly, bank-like wallets, which are inherently more user-friendly than their open-source counterparts, are correlated with a 71% lower cash out rate. Students in dorms have similar cash out rate than students outside of dorms. Students who expected the Bitcoin price to fall were 93% more likely to cash out. Students that were new to Bitcoin were 50% less likely to cash out. Students with a computer science background, probably because of lower learning costs, were 19% less likely to cash out. Our text on encryption ('Encryption Text Randomization'), possibly by reassuring some of the students about the safety of their data, causally reduced cashing out by approximately 27%. The random exposure to a matrix of trade-offs about different digital wallets in terms of government surveillance ('Surveillance Nudge Randomization') instead had little effect on the students' propensity to immediately cash out. A randomization targeted at nudging students to list their Bitcoin address in a public MIT directory ('Public Commitment Randomization') had a positive effect on retention, reducing cashing out by 29%, potentially because of the additional social pressure coming from having publicly embraced the technology. The long-term effects of this public commitment are something we intend to explore in future work.

Since these results are novel, we check their robustness to a variety of different measures.

First, we test whether or not our choice of a two-week window to define "immediate" cash out behavior is a sensible one. In Table 3, when we repeat our main specification using only same-day cashing out behavior in Column (1), we actually find even stronger results. Delayed early adopters are 5.5 times more likely to cash out than non-delayed, regular users. Results are consistent if we use a one week window as reported in Column (2), which suggests that early adopters are 2.2 times more likely to cash out. Column (3) reports the results for a broader window of three weeks and Column (4) reports the results for a four week window. At four weeks, delayed early adopters are still 64% more likely to immediately cashout.

Second, we also report in Table 3 further robustness checks that our use of the logit functional form does not drive our results. Columns (6) and (7) of Table 3 shows the robustness of our results to an OLS and Probit specification.

Table 2: Delaying Early Adopters Increases Their Cash Out Rate

VARIABLES	(1) Cash Out	(2) Cash Out	(3) Cash Out	(4) Cash Out	(5) Cash Out	(6) Cash Out
Early Adopter	1.5707***	1.1142	1.0381	1.0411	0.9441	0.9417
	(0.1931)	(0.2107)	(0.2001)	(0.2008)	(0.1825)	(0.1824)
Delayed		0.9578	0.9351	0.9333	0.9190	0.9225
		(0.1331)	(0.1322)	(0.1319)	(0.1313)	(0.1332)
Early Adopter × Delayed		1.8702**	1.9384***	1.9282***	1.9406***	1.9718***
		(0.4683)	(0.4939)	(0.4912)	(0.4969)	(0.5074)
Bank-Like Wallet			0.3286***	0.3286***	0.2903***	0.2853***
			(0.0384)	(0.0384)	(0.0353)	(0.0358)
Dorm				1.0877	1.0822	1.0775
				(0.1502)	(0.1513)	(0.1507)
Expected Price Decay					1.9424***	1.9314***
					(0.2647)	(0.2625)
New to Bitcoin					0.5061***	0.5017***
					(0.0895)	(0.0883)
Computer Science Student					0.8149	0.8130*
					(0.1023)	(0.1023)
Encryption Rand.						0.7251***
						(0.0862)
Surveillance Nudge Rand.						1.1036
						(0.1338)
Public Commitment Rand.						0.7164**
						(0.1044)
Constant	0.1095***	0.1119***	0.2286***	0.2149***	0.4059***	0.4961***
	(0.0076)	(0.0110)	(0.0270)	(0.0328)	(0.0957)	(0.1235)
Observations	3,108	3,108	3,108	3,108	3,108	3,108

Notes: Logit odds ratios reported. Sample is all MIT students who participated in the study and received bitcoin. Dependent variable is whether the student cashed out bitcoin within two weeks of receiving it. Robust Standard Errors reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.3 Considering Alternative Interpretations of Our Results

A potential interpretation of our results is that delayed early adopters were simply more difficult to track. For example, perhaps someone tech-savvy, such as more of our natural early adopters were, could have spent the two weeks before they received the bitcoin better understanding how to escape our surveillance relative to their peers in the first distribution.

Table 3: Robustness to Cash Out Window and Functional Form

VARIABLES	(1) Cash Out Same Day	(2) Cash Out 1 Week	(3) Cash Out 2 Weeks	(4) Cash Out 3 Weeks	(5) Cash Out 4 Weeks	(6) Cash Out OLS	(7) Cash Out Probit
Early Adopter	0.5501	0.9140	0.9417	0.8707	1.0117	-0.0050	-0.0376
	(0.2281)	(0.2083)	(0.1824)	(0.1614)	(0.1769)	(0.0178)	(0.1021)
Delayed	0.9231	0.9881	0.9225	0.9461	0.9881	-0.0070	-0.0461
	(0.2454)	(0.1650)	(0.1332)	(0.1264)	(0.1264)	(0.0122)	(0.0739)
Early Adopter × Delayed	5.4919***	2.1838***	1.9718***	2.0011***	1.6384**	0.0748***	0.3686***
	(2.7556)	(0.6454)	(0.5074)	(0.4895)	(0.3812)	(0.0273)	(0.1373)
Bank-Like Wallet	0.9438	0.3731***	0.2853***	0.3055***	0.3189***	-0.1316***	-0.6616***
	(0.2330)	(0.0530)	(0.0358)	(0.0360)	(0.0360)	(0.0146)	(0.0662)
Dorm	0.4771***	0.9080	1.0775	0.9519	0.9866	0.0082	0.0171
	(0.1030)	(0.1399)	(0.1507)	(0.1220)	(0.1216)	(0.0126)	(0.0724)
Expected Price Decay	2.9710***	2.2595***	1.9314***	1.9613***	1.8567***	0.0713***	0.3507***
	(0.6592)	(0.3385)	(0.2625)	(0.2521)	(0.2307)	(0.0168)	(0.0744)
New to Bitcoin	0.3955***	0.5142***	0.5017***	0.5108***	0.5177***	-0.0653***	-0.3602***
	(0.1045)	(0.1012)	(0.0883)	(0.0842)	(0.0816)	(0.0201)	(0.0943)
Computer Science Student	0.6593*	0.8015	0.8130*	0.8249	0.7826**	-0.0190*	-0.1051
	(0.1518)	(0.1154)	(0.1023)	(0.0970)	(0.0886)	(0.0115)	(0.0659)
Encryption Rand.	0.7798	0.6807***	0.7251***	0.7693**	0.7797**	-0.0297***	-0.1553**
	(0.1658)	(0.0931)	(0.0862)	(0.0857)	(0.0829)	(0.0110)	(0.0622)
Surveillance Nudge Rand.	1.1270	1.0290	1.1036	1.1142	1.1766	0.0075	0.0461
	(0.2466)	(0.1420)	(0.1338)	(0.1264)	(0.1272)	(0.0111)	(0.0635)
Public Commitment Rand.	0.6181*	0.7228*	0.7164**	0.7526**	0.7802*	-0.0286**	-0.1754**
	(0.1712)	(0.1223)	(0.1044)	(0.1017)	(0.1004)	(0.0118)	(0.0747)
Constant	0.1071***	0.3187***	0.4961***	0.5900**	0.6009**	0.2649***	-0.4650***
	(0.0411)	(0.0890)	(0.1235)	(0.1380)	(0.1363)	(0.0278)	(0.1338)
Observations	3,108	3,108	3,108	3,108	3,108	3,108	3,108
R-squared						0.055	

Notes: Logit odds ratios reported in Columns (1) to (5). Column (6) reports OLS estimates, and Column (7) reports Probit estimates. Sample is all MIT students who participated in the study and received bitcoin. Dependent variable is whether the student cashed out bitcoin the same day of receiving it in Column (1), within 1 week in Column (2), within 2 weeks in Column (3),(6) and (7), within 3 weeks in Column (4), and within 4 weeks in Column (5). Robust Standard Errors reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

To address this, we explore whether our choice to measure technology disadoption using transaction data from the wallet providers and the public Bitcoin blockchain is consistent with other measures of disadoption. Reassuringly, we find that our measure of cashing out does not vary in its consistency across earlier adopter status with students' responses regarding technology disadoption in their final survey response as can be seen in Figure 3.

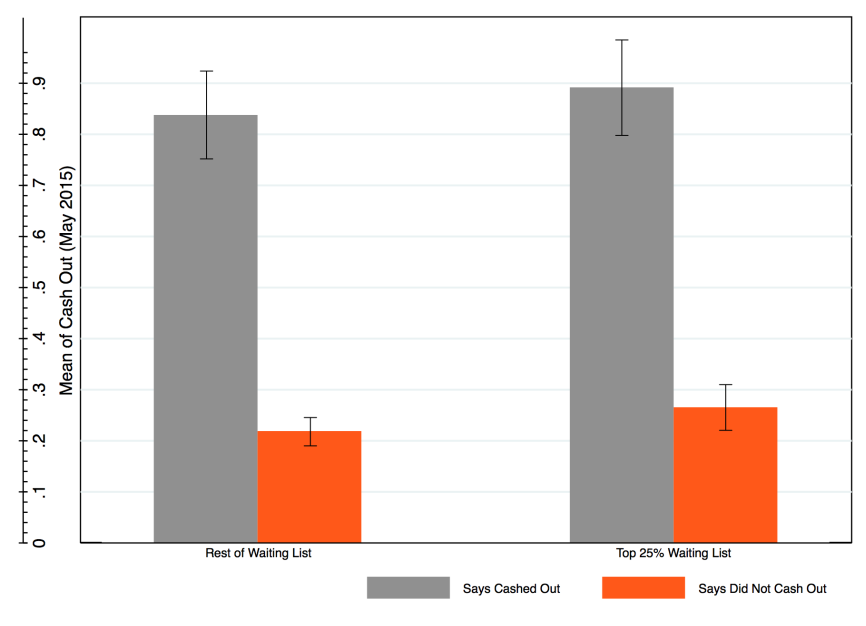


Figure 3: Transaction Data versus Survey Measures

Figure 3 does suggest that there is still a mismatch between the stated survey data and what we observed in the usage data. Therefore, since this approach relies on believing student's stated survey response, we also checked that our results replicate with a more easy to verify set of behavioral data. Here, we limited the sample to digital wallets for which we have perfect information on identity, because these particular wallets need to comply with Anti-Money Laundering and 'Know Your Customer' regulations. In the appendix, we repeat our analysis for Table 3, for this restricted subsample and report them as Table A-1. Possibly because these user friendly, bank-like wallets allow users to transfer money to and from a regular bank account in just a few, easy steps, the coefficient for delayed early adopters is largest and most significant for same-day cashing out behavior in Column (1) in Table A-1, but qualitatively comparable in direction and magnitude with the full sample in the other columns which test cashing out windows from 1 to 4 weeks even though the limited sample means that the estimates are not always significant.

Another alternative interpretation of our results is that our measure of being an early adopter simply meant that the person needed cash. The more we delayed such a person, the more likely they were to cash out immediately as their need for cash became more and more pressing. This concern reflects an unusual feature of our setting which is that disadoption actually has a direct upside in the form of cash. However, in Columns (1) and (2) of Table 4 we show that our main results are stronger, not weaker, when we focus only on students that are more likely to have financial resources such as students who had a credit card or had a paying internship. We also do not observe any systematic, statistically significant difference between students that carry above the median cash versus below the median cash in their wallets as can be seen in Columns (3) and (4) of Table 4.

Another alternative interpretation is that our early adopters already had Bitcoin wallets and that what we measure as 'cashing out' actually was just a transfer to an existing wallet. The delay may simply have allowed these existing Bitcoin users to plan such a transfer better. To investigate this, in Table 4 we split in Columns (5) and (6) our main sample by students who are new to Bitcoin versus not. We show that we still find the main effect when we restrict our sample to those who have not used Bitcoin before, suggesting it is not the existence of Bitcoin wallets among early adopters which drives our result. We do not observe such an effect for those who already have bitcoin though of course this is a small subsample - perhaps because they were already embedded in the system or else difficult to track.

Table 4: Robustness to Alternative Explanations

VARIABLES	(1) Financially Independent	(2) Others	(3) Above Median Cash	(4) Below Median Cash	(5) New to BTC	(6) Not New to BTC	(7) BTC Attractive as Investment	(8) Others
Early Adopter	0.7433	1.3608	0.9101	0.9786	0.8496	1.7605	0.5677	1.1619
	(0.1957)	(0.3955)	(0.2657)	(0.2553)	(0.1857)	(0.8592)	(0.2243)	(0.2613)
Delayed	0.9252	0.9355	0.9896	0.8721	0.8247	2.2562*	0.7601	0.9832
	(0.1753)	(0.2090)	(0.2239)	(0.1649)	(0.1265)	(1.0452)	(0.2057)	(0.1683)
Early Adopter × Delayed	2.1832**	1.7509	2.2308**	1.8066*	2.6116***	0.4640	3.6706***	1.5551
	(0.7490)	(0.6870)	(0.8488)	(0.6422)	(0.7508)	(0.2983)	(1.8432)	(0.4746)
Bank-Like Wallet	0.3531***	0.2179***	0.2214***	0.3426***	0.2893***	0.2511***	0.2246***	0.3189***
	(0.0590)	(0.0422)	(0.0436)	(0.0563)	(0.0382)	(0.1041)	(0.0551)	(0.0472)
Dorm	1.0384	1.1205	1.2189	1.0188	1.0637	1.1634	1.3415	0.9974
	(0.1801)	(0.2686)	(0.2806)	(0.1815)	(0.1618)	(0.4400)	(0.3774)	(0.1616)
Expected Price Decay	2.0279***	1.7588***	1.9287***	1.9084***	1.8289***	2.5571***	2.1285***	1.8087***
	(0.3579)	(0.3769)	(0.4038)	(0.3445)	(0.2759)	(0.8502)	(0.5805)	(0.2862)
New to Bitcoin	0.5824**	0.4469***	0.4471***	0.5431***			0.5201**	0.5004***
	(0.1337)	(0.1238)	(0.1215)	(0.1274)			(0.1688)	(0.1062)
Computer Science Student	1.0018	0.5926**	0.7850	0.8376	0.8785	0.5303**	0.5578**	0.9442
	(0.1627)	(0.1212)	(0.1490)	(0.1412)	(0.1192)	(0.1669)	(0.1381)	(0.1395)
Encryption Rand.	0.7460*	0.6852**	0.7096*	0.7348**	0.7394**	0.6310	0.6965	0.7301**
	(0.1171)	(0.1259)	(0.1300)	(0.1154)	(0.0951)	(0.2045)	(0.1543)	(0.1034)
Surveillance Nudge Rand.	1.0959	1.0950	1.3096	0.9619	1.0359	1.6675	1.2569	1.0522
	(0.1742)	(0.2087)	(0.2426)	(0.1554)	(0.1363)	(0.5476)	(0.3076)	(0.1483)
Public Commitment Rand.	0.7486	0.6780*	0.6617*	0.7762	0.7556*	0.5270	0.9800	0.6216***
	(0.1410)	(0.1599)	(0.1463)	(0.1517)	(0.1172)	(0.2290)	(0.2483)	(0.1119)
Constant	0.3634***	0.6833	0.4502**	0.5231**	0.2591***	0.3397*	0.4346*	0.5163**
	(0.1201)	(0.2664)	(0.1733)	(0.1725)	(0.0503)	(0.2111)	(0.1966)	(0.1540)
Observations	1,829	1,279	1,490	1,618	2,755	353	1,083	2,025

Notes: Logit odds ratios reported. Sample is all MIT students who participated in the study and received bitcoin. Dependent variable is whether the student cashed out bitcoin within two weeks of receiving it. In Columns (1) and (2), we classify students as more likely to have financial resources as students who have a credit card for discretionary purposes, or had internships the summer. In Columns (3) and (4), cash refers to the amount of USD students usually carry in their wallet. In Columns (5) and (6) we distinguish between students on the basis of prior Bitcoin adoption. Columns (7) and (8) are based on the students' stated preferences during sign up. Robust Standard Errors reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

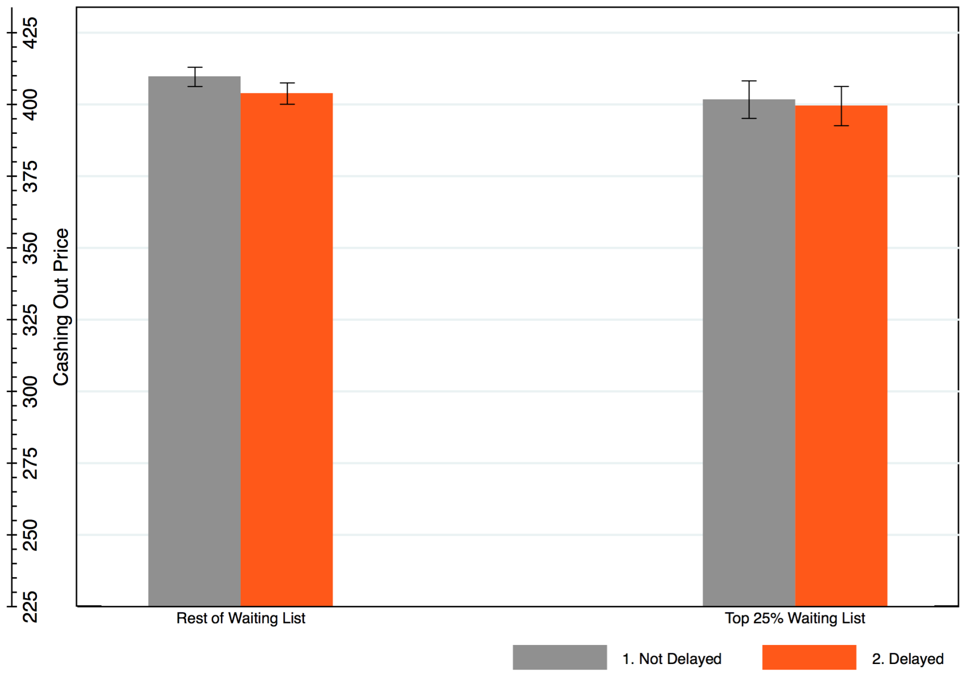


Figure 4: Early Adopters and Bitcoin Price at Cashing Out

There could also be other potential alternative explanations based on students' intended use for Bitcoin if there was some systematic distaste for holding on to it as a potential investment which was more pronounced for early adopters who had time to reflect. However, we show that our results are stronger when we focus on students who explicitly said they were interested in Bitcoin as an investment vehicle in Columns (7) and (8), that is, the precise students who had explicitly announced an intention to hold on to it before the distribution.

A final alternative explanation is 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, to address this we show that early adopters do not cash out on average at better prices than other students in Figure 4. This is perhaps not surprising given the high volatility of Bitcoin during the study period.

3.4 Understanding the Mechanism

Having ruled out multiple explanations for the results in Figure 2 and Table 2 that delaying natural early adopters encouraged them to leave the Bitcoin ecosystem, we now consider why it is that delays may have had this effect.

One potential explanation may be that early adopters derive utility from being first to adopt a technology. This may be tied simply to utility from feeling that they have 'early access' or may be because their identity also rests on being the first to try new technology.

To explore these class of identity-based explanations, we distinguished between environments where early adopters would know they were delayed and the fact would be obvious to them as their peers had already adopted relative to other environments where it would be less obvious. To do this we turned to the dorm structure at MIT. At MIT, dorms operate as social clusters. As highlighted at `https://housing.mit.edu/`, '[residences offer] a powerful sense of community. Every undergraduate and graduate residence offers its own rich social network, a distinct culture, lifestyle, and perspective.' Therefore we compare the behavior of students who live in these social clusters and those who do not, and also exploit across-dorm variation in the extent to which a dorm is tightly socially clustered.

The results are reported in Table 5. We find in Column (1) that the effect is not present for students that are living off campus relative to those who live within Campus. When we turn to within-campus variation, we see the effect is weaker in larger dorms in Column (3). We also see the effect is substantially more pronounced within smaller dorms in Column (4), where the observability of one's delay is likely to be stronger. The results suggest that delayed early adopters are 4.3 times more likely to cash out than non-delayed, regular users within dorms of below-median size. As before, results are robust to the inclusion of a number of controls such as the assignment to a dorm, the type of digital wallet selected by the students, the absence of past experience with Bitcoin, students' technical skills and expectations about the Bitcoin price, and other randomizations.

Table 5: Delaying Early Adopters Increases Their Cash Out Rate. Effect is Coming From Dorms, Particularly Small Ones.

VARIABLES	(1) Off Campus	(2) Dorms	(3) Dorms Above Median Size	(4) Dorms Below Median Size
Early Adopter	0.9647	0.9456	1.0094	0.9099
	(0.3416)	(0.2214)	(0.2716)	(0.4497)
Delayed	1.0044	0.9201	1.0019	0.7284
	(0.2712)	(0.1566)	(0.1993)	(0.2429)
Early Adopter × Delayed	1.2075	2.1520**	1.6735	4.3426**
	(0.6391)	(0.6466)	(0.5818)	(2.7198)
Bank-Like Wallet	0.7046	0.2123***	0.2188***	0.1983***
	(0.1794)	(0.0314)	(0.0375)	(0.0601)
Expected Price Decay	1.5963	2.1117***	2.4278***	1.2461
	(0.4630)	(0.3307)	(0.4459)	(0.3772)
New to Bitcoin	0.7237	0.4557***	0.4747***	0.3979**
	(0.2487)	(0.0957)	(0.1164)	(0.1687)
Computer Science Student	0.9187	0.7819*	0.7410*	0.8838
	(0.2279)	(0.1150)	(0.1302)	(0.2486)
Encryption Rand.	0.7689	0.7108**	0.6802**	0.7731
	(0.1797)	(0.0994)	(0.1119)	(0.2109)
Surveillance Nudge Rand.	0.8548	1.2179	1.2404	1.2354
	(0.2020)	(0.1731)	(0.2021)	(0.3695)
Public Commitment Rand.	0.4930**	0.8037	0.6492**	1.3735
	(0.1592)	(0.1334)	(0.1316)	(0.4166)
Constant	0.2554***	0.6137*	0.5674*	0.7685
	(0.1157)	(0.1703)	(0.1876)	(0.4075)
Observations	810	2,298	1,766	532

Notes: Logit odds ratios reported. Sample is all MIT students who participated in the study and received bitcoin. Dependent variable is whether the student cashed out bitcoin within two weeks of receiving it. 74% of students live in dorms, and the remaining 26% lives off campus. Dorms with more than 176 students are classified as above median size. Robust Standard Errors reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6 presents additional evidence that is consistent with the idea that the process whereby early adopters disadopt the technology if they are delayed is social in nature. Cashing out is higher in environments where early adopters are more likely to be scarce and unique. For example, we show the effect is higher for dorms with low density of pre-existing

Bitcoin adopters in Column (1), is higher in dorms with a low density of computer science students in Column (3), and is also higher in dorms with low density of early adopters themselves Column (5). The effect is small and insignificant in cases where multiple technological leaders are likely to co-exist with others, as can be seen in Columns (2), (4) and (6).

Table 6: Above and Below the Median Density of Early Bitcoin Users, Tech Talent and Early Adopters in Dorms.

VARIABLES	(1) Dorms Below Median BTC Adopters	(2) Dorms Above Median BTC Adopters	(3) Dorms Below Median CS Students	(4) Dorms Above Median CS Students	(5) Dorms Below Median Early Adopters	(6) Dorms Above Median Early Adopters
Early Adopter	0.6993	1.1606	1.0516	0.8899	0.2620*	1.1462
	(0.2787)	(0.3547)	(0.3430)	(0.3026)	(0.2043)	(0.3221)
Delayed	0.6928	1.1754	0.7524	1.0787	0.8193	1.0053
	(0.1738)	(0.2748)	(0.1909)	(0.2486)	(0.1945)	(0.2493)
Early Adopter × Delayed	4.5043***	1.2834	3.5593***	1.1530	9.7229***	1.6059
	(2.2064)	(0.5037)	(1.5009)	(0.5077)	(8.3787)	(0.5852)
Bank-Like Wallet	0.2248***	0.2023***	0.2399***	0.1970***	0.2957***	0.1735***
	(0.0513)	(0.0396)	(0.0509)	(0.0412)	(0.0689)	(0.0342)
Expected Price Decay	1.6792**	2.4970***	1.3833	2.8954***	2.2183***	2.1131***
	(0.4395)	(0.5088)	(0.3348)	(0.6057)	(0.5514)	(0.4348)
New to Bitcoin	0.5771	0.4361***	0.4424**	0.4312***	0.6513	0.3865***
	(0.3939)	(0.1018)	(0.1466)	(0.1187)	(0.2607)	(0.1000)
Computer Science Student	0.5400**	1.0171	0.8946	0.8521	0.6368*	0.8757
	(0.1310)	(0.1949)	(0.2242)	(0.1709)	(0.1539)	(0.1642)
Encryption Rand.	0.8969	0.5829***	0.7818	0.6418**	0.6086**	0.7633
	(0.1882)	(0.1114)	(0.1552)	(0.1278)	(0.1367)	(0.1395)
Surveillance Nudge Rand.	1.0465	1.4051*	1.4005*	1.0696	1.0139	1.3164
	(0.2292)	(0.2675)	(0.2815)	(0.2170)	(0.2310)	(0.2396)
Public Commitment Rand.	0.8650	0.7696	0.7053	0.9133	0.8908	0.7408
	(0.2142)	(0.1755)	(0.1849)	(0.2027)	(0.2298)	(0.1639)
Constant	0.5999	0.5057*	0.6393	0.5732	0.4642*	0.6882
	(0.4520)	(0.1784)	(0.2636)	(0.2208)	(0.2055)	(0.2664)
Observations	1,018	1,280	993	1,305	1,021	1,277

Notes: Logit odds ratios reported. Sample is all MIT students who participated in the study and received bitcoin. Dependent variable is whether the student cashed out bitcoin within two weeks of receiving it. In Columns (1) and (2), Bitcoin Adopters are defined as students who have used Bitcoin before the MIT study started. In Columns (3) and (4) we distinguish between Dorms with below and above median density of computer science students. In Columns (5) and (6), Early Adopters are defined as in the previous tables as the top 25% of the waitlist. Robust Standard Errors reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

One alternative explanation for these results is that rather than a need for visible uniqueness among early adopters, the random delay limited the ability of others to properly learn from their generally superior technology skills and that there was more likely to be such technology transfer in smaller dorms. This meant that by the time early adopters received their bitcoin, the adoption process had unraveled, leaving them with no option but to disadopt the technology. However, in Figure 5, we show that delayed early adopters' cash out rate is high even when none of their friends have cashed out, which is consistent with their decision being unrelated to the exit decision of their peers.

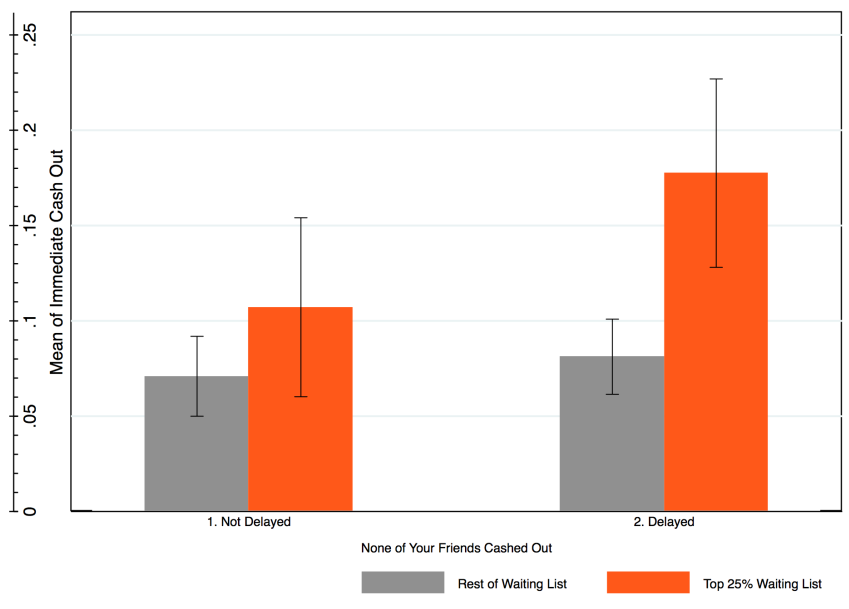
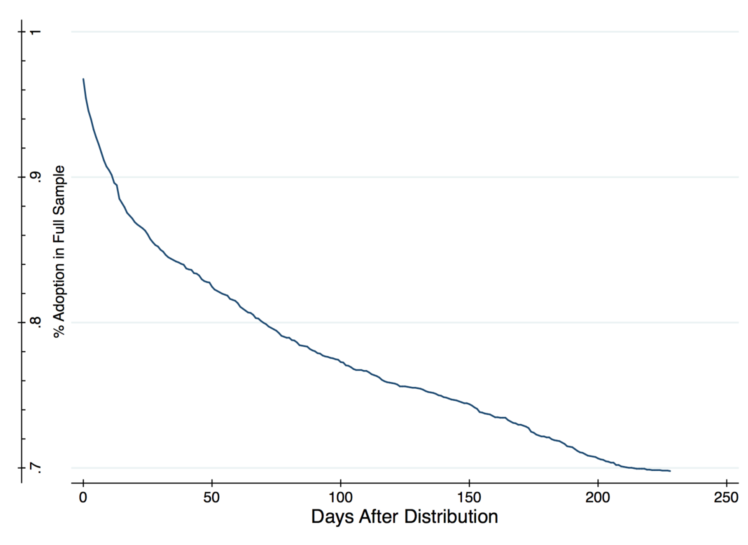


Figure 5: Isolating Analysis to Cases where No Friends Cashed Out

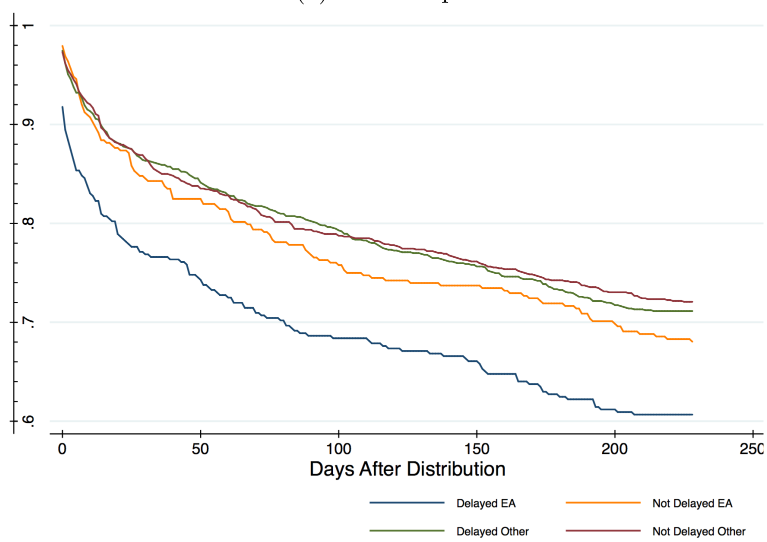
3.5 Spillovers of Disadoption to Others

To test if disadoption by delayed natural 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 disadoption across different subpopulations in our sample over a longer period.

Figure 6a shows the aggregate disadoption rate in the full sample, and Figure 6b splits the sample by early adopters versus not and delayed versus not: Whereas non-delayed early adopters exhibit a similar pattern to other users, 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.



(a) Full Sample

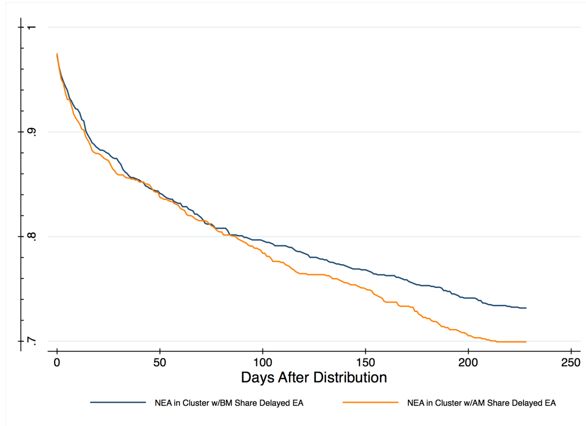


(b) Early Adopters versus Not, Delayed versus Not

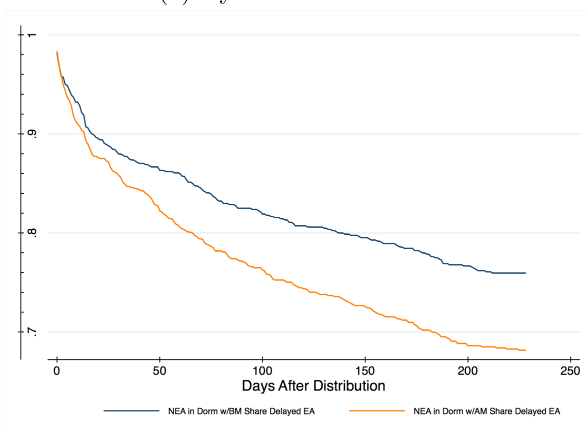
Figure 6: Disadoption Curve

However, there is also the potential that the decisions of early adopters to disadopt the technology also have spillovers on their peers who perhaps rely on them to learn how to use the technology or else simply follow their lead in technology matters. To see if disadoption prompted by the delaying natural early adopters generated negative spillovers on their peers, we look at long-run disadoption by non-early-adopters - referred to as NEA. Figure 7a) splits the sample by whether the grouping of friends had an above the median or below the median share of delayed early adopters. At a more aggregate scale, Figure 7b also compares dorms with an above the median versus below the median share of delayed early adopters. The results are consistent with the presence of spillovers: The lines which represent social clusters or dorms with a larger share of delayed early adopters, decay at a faster rate than those with a lower share. The results are magnified when students are geographically proximate as they are in small dorms or in the same dorm and floor, as can be seen in Figure 7c and 7d.

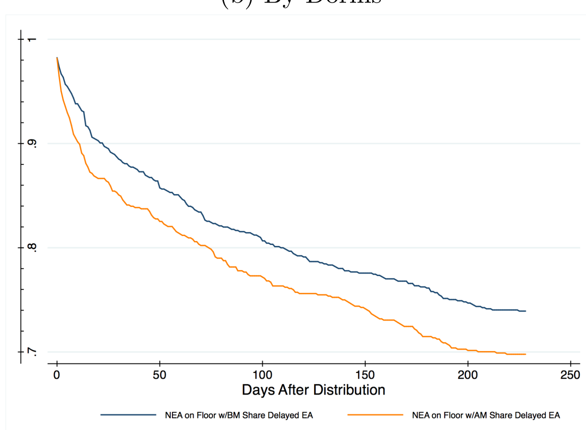
A natural final question is whether this phenomenon also translates to usage - not just the discrete decision to reject the technology. Higher exit or disadoption by natural early adopters also corresponds to lower Bitcoin activity, not only to disadoption: In Figure 8, we build diffusion S-curves by 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 an above the median share of early adopters were delayed are 45% less active than other dorms.



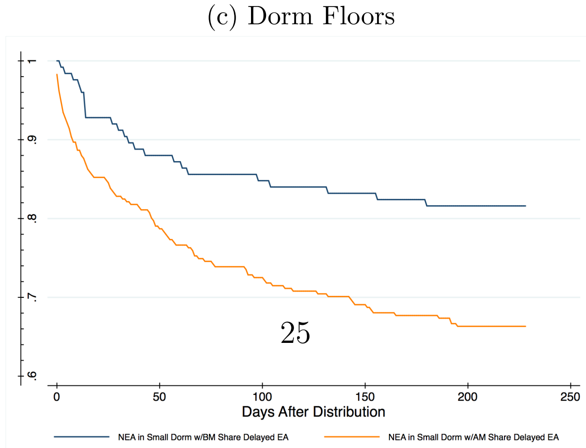
(a) By Network Clusters



(b) By Dorms



(c) Dorm Floors



(d) Small Dorm

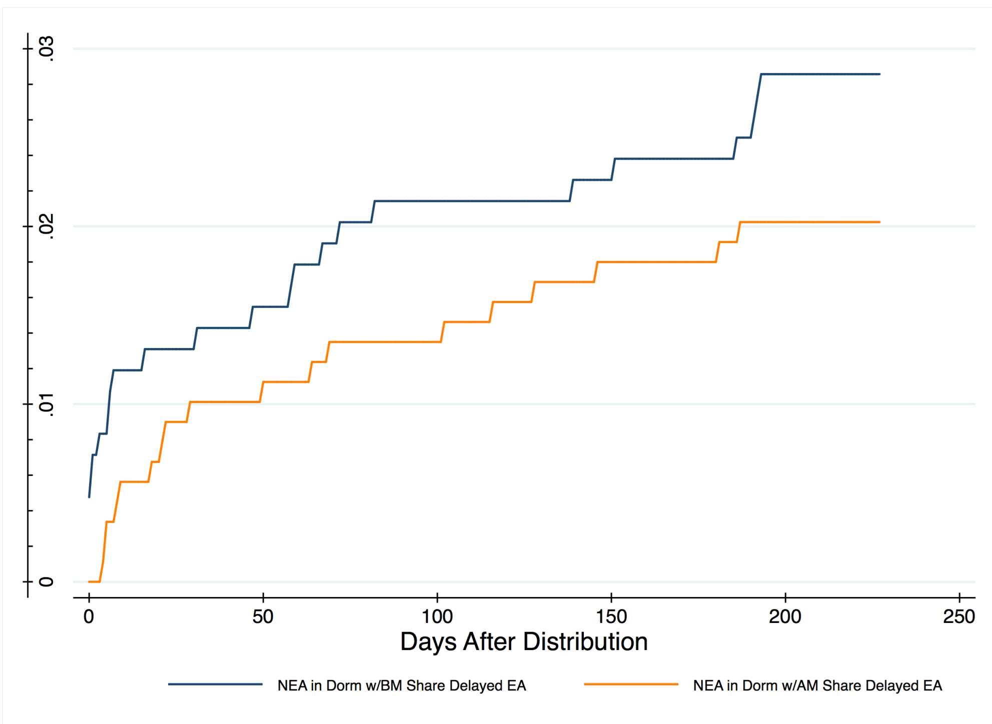


Figure 8: Technology S-Curves: Share Active (Received Additional Bitcoin)

4 Conclusion

Early adopters, with their preferences, needs, and attitude towards risk, influence not only how information about a new technology is acquired, 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 early adopters' positive, network-effect-building role, our results highlight a case where they might be obstructing further diffusion if they refuse to adopt because their desire to feel unique is challenged.

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 reduced the consumption utility they derive from early access. Because of the demographic involved in the study and setting of college students in dorms, the 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,[4] where Google, 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 community of developers who expected early access, and consequently alienated the technology community. Similarly, crowdfunding projects have run into problems when the early adopters who had funded them received the product after regular customers and a waitlist was not honored.[5]

[4]See `http://www.nytimes.com/2015/02/05/style/why-google-glass-broke.html` (accessed 01-28-2).

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

There are of course limitations to our study. First, we are studying the diffusion of a unique technology which not only does not have a clear use case but is also more complex than many technologies, since it can be used both as a vehicle for transactions or an investment vehicle. Second, we are studying the diffusion of Bitcoin in the unique community of MIT. Third, because the experiment we study essentially gave everyone the technology, our dependent variable is disadoption rather than the more classic adoption. Fourth, we do not have variation in the length of delay that early adopters experience, so cannot give guidance as to optimal delay strategies. Notwithstanding these limitations, the experimental nature of our data, combined with information on individual's behavior towards the technology, allows us for the first time to cleanly estimate the causal effect of short delays such as two weeks on adoption, and to calculate counterfactual diffusion curves. 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 a technology while ignoring early adopters' needs for distinctiveness is counterproductive.

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A Appendix

Table A-1: Bank-Like Wallets Only

	(1)	(2)	(3)	(4)	(5)
	Cash Out	Cash Out	Cash Out	Cash Out	Cash Out
	Bank-Like	Bank-Like	Bank-Like	Bank-Like	Bank-Like
VARIABLES	Same Day	1 Week	2 Weeks	3 Weeks	4 Weeks
Early Adopter	0.3671*	0.7436	0.9698	0.8961	1.1061
	(0.1942)	(0.2327)	(0.2654)	(0.2289)	(0.2579)
Delayed	0.9117	0.8493	1.0127	0.9534	0.9977
	(0.2640)	(0.1827)	(0.1965)	(0.1698)	(0.1684)
Early Adopter × Delayed	4.8220**	1.8775	1.4501	1.7225	1.3318
	(3.0618)	(0.7895)	(0.5338)	(0.5837)	(0.4196)
Dorm	0.3327***	0.5654***	0.6856**	0.6525***	0.7188**
	(0.0835)	(0.1092)	(0.1218)	(0.1054)	(0.1114)
Expected Price Decay	3.1993***	2.6234***	2.2536***	2.0937***	1.9050***
	(0.8371)	(0.5155)	(0.4051)	(0.3530)	(0.3082)
New to Bitcoin	0.4115***	0.4699***	0.4925***	0.5025***	0.5348***
	(0.1163)	(0.1052)	(0.1001)	(0.0940)	(0.0961)
Computer Science Student	0.8079	0.7168*	0.7965	0.7370*	0.7141**
	(0.2151)	(0.1451)	(0.1426)	(0.1225)	(0.1120)
Encryption Rand.	0.8482	0.7546	0.8037	0.8625	0.8959
	(0.2108)	(0.1384)	(0.1325)	(0.1304)	(0.1271)
Surveillance Nudge Rand.	1.1102	1.0745	1.0704	1.1128	1.2430
	(0.2786)	(0.1987)	(0.1779)	(0.1701)	(0.1802)
Public Commitment Rand.	0.5777*	0.5251***	0.5524***	0.6187**	0.6802**
	(0.1888)	(0.1305)	(0.1192)	(0.1194)	(0.1207)
Constant	0.1279***	0.2044***	0.1951***	0.2433***	0.2246***
	(0.0484)	(0.0626)	(0.0551)	(0.0637)	(0.0572)
Observations	2,217	2,217	2,217	2,217	2,217

Notes: Logit odds ratios reported. Sample is all MIT students who participated in the study, received bitcoin, and selected a bank-like wallet as their digital wallet. Dependent variable is whether the student cashed out bitcoin the same day of receiving it in Column (1), within 1 week in Column (2), within 2 weeks in Column (3), within 3 weeks in Column (4), and within 4 weeks in Column (5). Robust Standard Errors reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$