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Currency substitution in the shadow economy: International panel evidence using local Bitcoin trade volume ☆

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ABSTRACT

While mainstream adoption of cryptocurrency as a replacement for traditional fiat money has yet to be realized, anecdotal evidence suggests that such substitution is more pervasive in the shadow economy. I test this hypothesis by exploiting cross-country shadow market variation and exogenous shocks to darknet marketplaces used exclusively for illegal transactions in 28 emerging market economies. I find that Bitcoin trade volume generated by underground activity reacts much more strongly to inflation expectations than Bitcoin trade volume among the general population, providing direct evidence that shadow market participants substitute away from cash and towards cryptocurrency to conduct anonymous transactions. This effect is particularly strong among countries experiencing high annual inflation.

1. Introduction

The last decade has seen a rapid proliferation of interest in cryptocurrencies, leading many to speculate whether decentralized digital currency can compete with traditional fiat money as a medium of exchange. While excessive volatility makes it unlikely that the general public will widely adopt cryptocurrencies for transaction purposes anytime soon, there is one sector where such a decentralized payment method is enticing enough to compensate for the excess volatility: the underground "shadow" economy, where anonymous transactions are often prioritized to evade authorities. This increased reliance on anonymity suggests that shadow market participants view decentralized currency and fiat currency as closer substitutes than the general population, implying that underground cryptocurrency demand should be particularly sensitive to domestic inflation.

With this hypothesis in mind, I explore whether local Bitcoin trading is more sensitive to inflation expectations when shadow market activity is high using a weekly panel of 28 emerging market economies from 2013 to 2015, a period where the proportion of Bitcoin used for underground transactions was still at its peak (Foley et al., 2019). To account for confounding factors correlated with shadow economy size, I exploit one of the few instances of abnormal Bitcoin trading known to be specifically driven by underground transactions: law-enforcement seizures and closures of darknet marketplaces (Foley et al., 2019). Using a quasi-experimental specification similar to a difference-in-difference-in-differences design, I find that there is indeed currency substitution among likely shadow market participants, particularly in countries experiencing high annual inflation. These results contribute to the growing literature on currency substitution between traditional fiat money and cryptocurrency (Garratt and Wallace, 2018; Bolt and van Oordt, 2019; Fernandez-Villaverde and Sanches, 2019; Schilling and Uhlig, 2019), and is to my knowledge the first paper to identify such substitution through the effect of inflation expectations on underground Bitcoin demand.

2. Data

The dataset consists of an unbalanced weekly panel of 28 emerging economies from March 10, 2013 to December 26, 2015, which corresponds to the time period where currency-specific Bitcoin trade volume data is available but the proportion of Bitcoin trading associated with illegal underground activity is still at its height (Foley et al., 2019). Countries included in the sample had to be classified as either an emerging or frontier economy according to the MSCI Global Market Accessibility Review. The emphasis on developing nations, whose sovereign national

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Table 1
Emerging economies.

Country	Ticker	Shadow size	Bitcoin volume	Inflation rate
Argentina	MERVAL	22.86%	1.49	24.20%
Brazil	IBOV	33.60%	0.17	7.19%
Chile	IPSA	12.89%	0.90	3.62%
China	SHCOMP	12.03%	0.10	1.99%
Colombia	COLCAP	26.00%	0.47	3.30%
Croatia	CRO	24.24%	3.27	0.51%
Czech Republic	PX	11.00%	1.89	0.70%
Hungary	BUX	20.97%	0.63	0.48%
India	NIFTY	18.11%	0.08	7.71%
Indonesia	JCI	21.58%	0.01	6.39%
Kenya	NSEASI	30.70%	0.29	6.39%
Malaysia	FBMKLCI	27.44%	2.30	2.45%
Mexico	MEXBOL	29.09%	0.65	3.52%
Nigeria	NGSEINDX	51.61%	0.02	8.52%
Pakistan	KSE100	30.84%	0.10	5.80%
Peru	SPBLPGPT	40.41%	0.39	3.20%
Philippines	PCOMP	29.68%	0.47	2.28%
Poland	WIG	17.87%	0.99	0.06%
Romania	BET	23.21%	3.18	1.49%
Russia	IMOEX	32.32%	6.04	10.03%
Saudi Arabia	SASEIDX	14.06%	0.15	2.32%
South Africa	JALSHTR	21.59%	5.65	2.32%
South Korea	KOSPI	20.49%	0.08	1.09%
Thailand	SET	45.70%	2.94	1.06%
Turkey	XU100T	27.40%	0.04	8.01%
UAE	ADSMI	22.91%	1.93	2.51%
Ukraine	PFTS	40.95%	0.27	20.18%
Vietnam	VNINDEX	15.22%	0.04	3.77%

Table 1 presents the 28 emerging economies in the sample, along with their corresponding stock market index tickers from Bloomberg Terminals used in the analysis, average shadow economy size as a percentage of GDP from 2013 to 2015 taken from Medina and Schneider (2018), average Bitcoin trade volume per million inhabitants (in BTC) taken from https://coin.dance, and average annual inflation rates from 2013 to 2015 taken from the World Bank.

currency is largely confined to within the country's borders, allows me to match currency-specific Bitcoin trade volume data to other country-level statistics. Moreover, emerging and frontier economies have relatively limited access to capital markets, including foreign currency exchanges, so that access to payment options insulated from domestic inflation is likely restricted.

The second criteria for country inclusion was having weekly Bitcoin trade volume observations during the sample period on https://coin.dance, which reports currency-specific weekly fiat-to-Bitcoin transaction volume from LocalBitcoins, a peer-to-peer Bitcoin marketplace based in Finland that facilitates OTC Bitcoin trades.[1,2] LocalBitcoins exhibits several features that make it ideally suited for shadow market activity during the sample period, including large transaction costs (which deter high-frequency speculation), shorter wait times, greater anonymity, and a relatively lax regulatory environment.[3] A strong association between LocalBitcoins volume and shadow activity is anecdotally supported by several high-profile money laundering arrests of LocalBitcoins users during the sample period, and, more recently, by evidence suggesting that over 99% of Bitcoin funds coming from criminal sources were received through LocalBitcoins.[4,5]

Following Guzman (2011), who finds that inflation Google search intensity is a better indicator of inflation expectations than more traditional measures at lower frequencies, I capture local inflation concerns with weekly Google search volume index (SVI) data for the term "inflation" in each country extracted from Google Trends, which tracks the relative frequency of Google search intensity for a given term in a specific time and location as a proportion of all searches.[6] Furthermore, to control for mainstream Bitcoin attention, the analysis also utilizes weekly Google Trends SVI data for the term "Bitcoin", which Foley et al. (2019) find is inversely related to the proportion of Bitcoin activity by criminal users and is also known to influence future trade volume (Katsiampa et al., 2019).

To measure shadow economic activity in each country, I rely on the annual shadow economy figures reported in Medina and Schneider (2018), which are extrapolated by imposing a structural equation between variables thought to cause shadow economic activity and variables thought to indicate shadow economic activity. Finally, to control for country-specific financial market performance, the analysis utilizes benchmark stock market index data for each country, taken from Bloomberg Terminals. Table 1 presents each of the 28 emerging economies used in the sample, along with their stock market index tickers and select country averages.

3. Analysis

3.1. Methodology

If shadow market participants seek Bitcoin as an alternative to national currency for anonymous transactions, Bitcoin trading

1 The starting dates for fiat-to-Bitcoin volume pairs on coin.dance range from the week ending on March 16, 2013 to the week ending on February 22, 2014, resulting in an unbalanced panel.

2 Kazakhstan was excluded from the analysis due to a lack of consistent trade volume observations on coin.dance until the end of 2015.

3 https://medium.com/@mattahlborg/nuanced-analysis-of-localbitcoins-data-suggests-bitcoin-is-working-as-satoshi-intended-d8b04d3ac7b2.

4 https://www.dailydot.com/unclick/three-arrested-first-bitcoin-money-laundering/.

5 https://www.crowdfundinsider.com/2020/12/169976-p2p-bitcoin-exchange-localbitcoins-reports-that-russia-venezuela-colombia-are-among-its-main-markets-with-most-btc-trading-activity/#:~:text=Finnish%20exchanges%20ranked%20%231%20for,99%25%20of%20these%20criminal%20funds.

6 Each Google Trends SVI observation is normalized to be between 0 and 100, where 100 is the largest relative search frequency across the requested query.

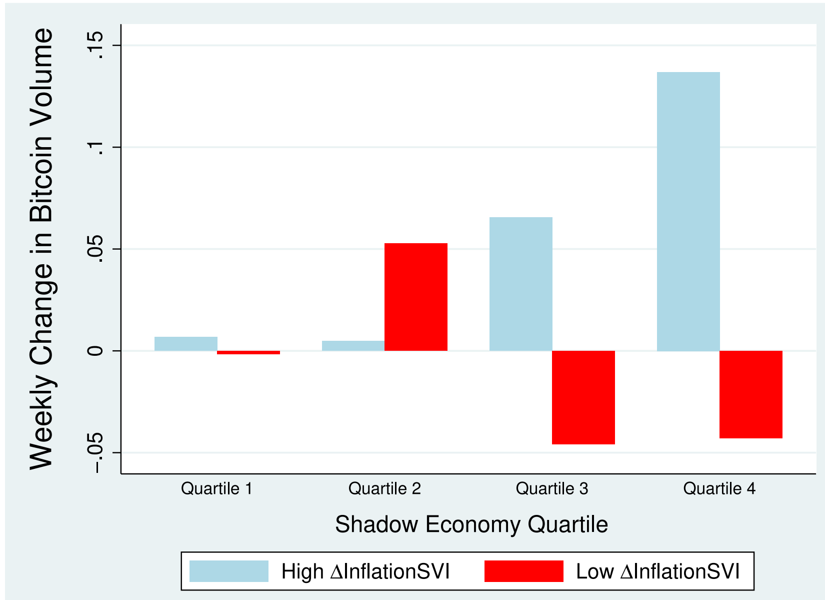

Fig. 1. Effect of Inflation SVI on Bitcoin Trade Volume By Shadow Economy Size. Fig. 1 presents average values of the weekly change in Bitcoin trade volume (per million), broken down by shadow economy size quartile and by whether the weekly change in national Google SVI for "inflation" is above or below its median sample value.

Table 2
Darknet shock dates.

Date	Shock	Marketplace name
July 23, 2013	Individual Bitcoin seizure	n/a
August 27, 2013	Individual Bitcoin seizure	n/a
October 1, 2013	Individual Bitcoin seizure	n/a
October 2, 2013	Darknet closure and Bitcoin seizure	Silk Road I
November 29, 2013	Darknet closure	Sheep
February 17, 2014	Darknet closure	BuyItNow
August 15, 2014	Darknet closure	Pirate Market
August 19, 2014	Darknet closure	Pandora
November 5, 2014	Darknet closure	Silk Road 2
November 9, 2014	Darknet closure	The Marketplace
November 18, 2014	Darknet closure	Andromeda
March 14, 2015	Darknet closure	Evolution
May 18, 2015	Darknet closure	BlackBank
September 6, 2015	Darknet closure	Agora
October 14, 2015	Darknet closure	Mr Nice Guy 2
November 4, 2015	Darknet closure	Middle Earth
November 5, 2015	Darknet closure	Abraxas

Table 2 reports darknet marketplace shock dates used to calculate *Darknet*, including seizures of darknet marketplaces by law-enforcement agencies and marketplace closures. All dates are taken from Foley et al. (2019).

should be particularly sensitive to inflation expectations in high-shadow countries. This hypothesis is supported by Fig. 1, which demonstrates that only in the two largest shadow economy quartiles is an above-median increase (decrease) in inflation attention associated with a large positive (negative) Bitcoin trade volume reaction. Of course, it is difficult to give a causal interpretation to Fig. 1, as shadow market activity is clearly correlated with other factors affecting the inflation elasticity of Bitcoin demand, including financial development (Blackburn et al., 2012), cash use in the overall economy (Onnis and Tirelli, 2015), and banking system access (Bouraoui, 2020). Therefore, in order to identify currency substitution in the underground economy, I exploit law-enforcement seizures and closures of darknet marketplaces, which required criminal users to reallocate their Bitcoin holdings to alternative marketplaces (Foley et al., 2019).

Table 2 presents all darknet seizures and closures over the sample period. Since darknet websites primarily function as shadow marketplaces, they should have disproportionate effects on local Bitcoin volume in high-shadow economies. This is corroborated by Fig. 2, which shows that mean Bitcoin volume increases on the exact week of a darknet shock in high-shadow economies, whereas in low-shadow economies, abnormally high Bitcoin trading is not observed until the following week, when media coverage intensifies and word-of-mouth usually spreads.

Since previous literature and Fig. 2 both suggest that darknet events are capturing exogenous shocks to underground Bitcoin demand, these events can be used to identify whether underground Bitcoin demand is sensitive to inflation expectations. To

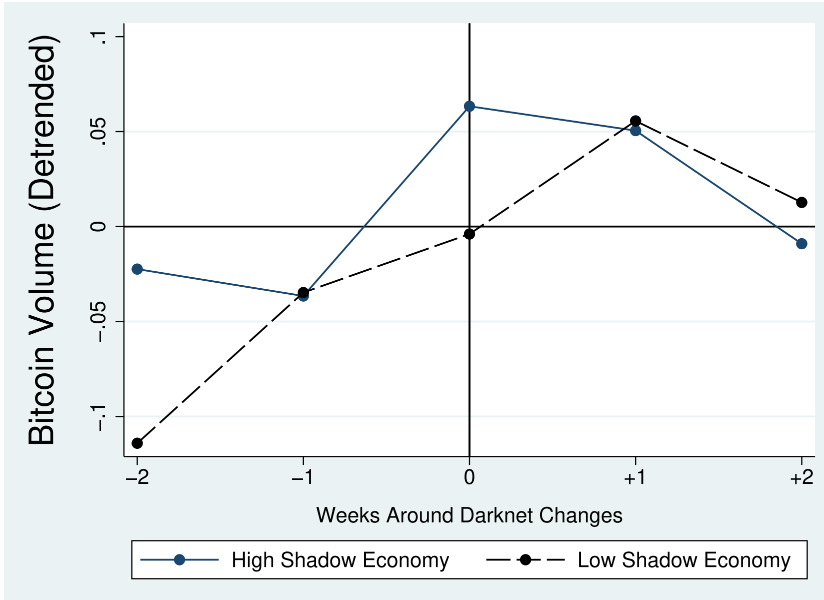

Fig. 2. Bitcoin Trade Volume Around Darknet Shocks. Fig. 2 presents average values of Bitcoin trade volume per capita around darknet market shocks (reported in Table 2), broken down by whether shadow market activity per capita is above or below its median sample value. Bitcoin trade volume is detrended by its median value over the previous 4 weeks.

do so, I estimate the following panel regression:

$$\begin{aligned}\Delta AbBitcoinVol_{i,t} = & \sum_{j=0}^{j=3} \alpha_j InflationSVI_{i,t-j} + \sum_{j=0}^{j=3} \beta_j Shadow_{i,t-j} \\ & + \sum_{j=0}^{j=3} \gamma_j InflationSVI_{i,t-j} \times Shadow_{i,t-j} \\ & + \sum_{j=0}^{j=3} \delta_j InflationSVI_{i,t-j} \times Darknet_{t-j} \\ & + \sum_{j=0}^{j=3} \alpha_j Shadow_{i,t-j} \times Darknet_{t-j} \\ & + \sum_{j=0}^{j=3} \iota_j InflationSVI_{i,t-j} \times Shadow_{i,t-j} \times Darknet_{t-j} \\ & + \zeta_1 Controls + \lambda_t + \theta_i + e_{i,t} \qquad (1)\end{aligned}$$

where $AbBitcoinVol_{i,t}$ is the natural log of abnormal Bitcoin volume per capita for country i during week t, $InflationSVI_{i,t}$ is the natural log of national Google search intensity for the term "inflation" in country i during week t, $Shadow_{i,t}$ is the size of country i's shadow economy as a percentage of GDP during week t, and $Darknet_t$ is an indicator for whether a darknet marketplace shock occurs during week t.[7,8] Similar in specification to a difference-in-difference-in-differences estimator, the main coefficient of interest, ι_0, makes use of both cross-country shadow size variation and the timing of exogenous darknet marketplace changes. Insomuch as Bitcoin trading spikes during darknet shock weeks are driven specifically by illegal activity, ι_0 captures currency substitution in underground markets, as it measures whether the inflation sensitivity of Bitcoin demand to shadow market activity is elevated during known periods of abnormal underground Bitcoin transactions.

3.2. Results

Table 3 reports the estimation of Eq. (1). In the case of the full specification estimated using the total sample, the relation between inflation sensitivity of local Bitcoin demand and shadow economic activity is nearly three times larger during darknet shock events, as captured by the contemporaneous triple interaction between *InflationSVI*, *Shadow*, and *Darknet*, going from 0.0115 to 0.0344. Since darknet closures and seizures exclusively affect underground activity, this effect is likely capturing underground market participants substituting away from cash and towards Bitcoin. In further support of this interpretation, Table 3 also reports that the contemporaneous triple interaction term is only significant among countries experiencing high annual inflation, which is expected given that inflation attentiveness is stronger in high-inflation environments (Coibion et al., 2020).

4. Conclusion

In this paper, I find that underground Bitcoin demand is sensitive to local inflation concerns, implying that cash and cryptocurrencies are close substitutes in the shadow economy. This result suggests that policies intended to curb illegal activity by eliminating cash will be ineffective as long as cryptocurrency is widely available, in agreement with Hendrickson and Luther (2021), thus providing some justification for governments to prohibit their use.

Since Foley et al. (2019) find that the relative proportion of Bitcoin transactions used for underground activity has declined in recent years, an interesting extension would be to examine whether the Bitcoin volume reaction documented in this paper has recently carried over to newer more opaque cryptocurrencies out of the public eye. Such an analysis could shed new light on whether currency substitution in the shadow economy has been accelerated by recent demonetization efforts (Rogoff, 2017).

[7] Abnormal Bitcoin is defined as the ratio of Bitcoin volume to its median value over the previous 4 weeks.

[8] *Darknet* in the absence of an interaction term is excluded from Eq. (1) due to the presence of time fixed effects.

Table 3
Panel regression results.

Dependent variable: $\Delta AbBitcoinVol_{i,t}$				
	Total sample	Total sample	Low inflation countries	High inflation countries
$InflationSVI_{i,t}$	−0.2628**	−0.2304*	−0.2978**	−0.3894
	(0.1080)	(0.1264)	(0.1272)	(0.3881)
$InflationSVI_{i,t-1}$	0.1415	0.0702	0.0379	0.5560*
	(0.1002)	(0.1013)	(0.0938)	(0.2763)
$InflationSVI_{i,t-2}$	0.1398	0.1416	0.2986**	−0.5549*
	(0.1571)	(0.1423)	(0.0984)	(0.2898)
$InflationSVI_{i,t-3}$	−0.2734*	−0.2225*	−0.3535*	0.2386
	(0.1417)	(0.1249)	(0.1683)	(0.1511)
$Shadow_{i,t}$	−0.1387	−0.1364	−0.1421	0.0230
	(0.1443)	(0.1450)	(0.2620)	(0.1951)
$Shadow_{i,t-1}$	0.1737	0.1776	0.2256	0.0025
	(0.2288)	(0.2310)	(0.4547)	(0.2627)
$Shadow_{i,t-2}$	−0.1292	−0.1378	−0.0842	−0.2450
	(0.1516)	(0.1549)	(0.3466)	(0.1931)
$Shadow_{i,t-3}$	0.0502	0.0576	−0.0682	0.2019
	(0.0831)	(0.0854)	(0.1340)	(0.1605)
$InflationSVI_{i,t} \times Shadow_{i,t}$	0.0128**	0.0115*	0.0138**	0.0150
	(0.0052)	(0.0061)	(0.0062)	(0.0149)
$InflationSVI_{i,t-1} \times Shadow_{i,t-1}$	−0.0049	−0.0019	0.0002	−0.0122
	(0.0048)	(0.0050)	(0.0049)	(0.0101)
$InflationSVI_{i,t-2} \times Shadow_{i,t-2}$	−0.0077	−0.0088	−0.0162***	0.0099
	(0.0075)	(0.0067)	(0.0042)	(0.011)
$InflationSVI_{i,t-3} \times Shadow_{i,t-3}$	0.0112	0.0099	0.0163	−0.0062
	(0.0069)	(0.0064)	(0.0099)	(0.0055)
$InflationSVI_{i,t} \times Darknet_t$		−0.5339***	−0.3697	−2.0030
		(0.1817)	(0.2272)	(1.1595)
$InflationSVI_{i,t-1} \times Darknet_{t-1}$		0.5495***	0.5669**	0.3944
		(0.1807)	(0.2222)	(0.9730)
$InflationSVI_{i,t-2} \times Darknet_{t-2}$		0.0401	0.1589	−0.4416
		(0.1598)	(0.1455)	(0.9955)
$InflationSVI_{i,t-3} \times Darknet_{t-3}$		−0.3439	−0.5784**	0.9919
		(0.2510)	(0.1975)	(0.7631)
$Shadow_{i,t} \times Darknet_t$		−0.0951***	−0.0729*	−0.2703*
		(0.0291)	(0.0387)	(0.1388)
$Shadow_{i,t-1} \times Darknet_{t-1}$		0.0587**	0.0730*	0.0527
		(0.0283)	(0.0404)	(0.1125)
$Shadow_{i,t-2} \times Darknet_{t-2}$		−0.0401	0.0131	−0.1259
		(0.0267)	(0.0496)	(0.1132)
$Shadow_{i,t-3} \times Darknet_{t-3}$		−0.0077	−0.0899	0.1567*
		(0.0523)	(0.0590)	(0.0811)
$InflationSVI_{i,t} \times Shadow_{i,t} \times Darknet_t$		0.0229**	0.0173	0.0725*
		(0.0087)	(0.0109)	(0.0396)
$InflationSVI_{i,t-1} \times Shadow_{i,t-1} \times Darknet_{t-1}$		−0.0198**	−0.0232*	−0.0192
		(0.0083)	(0.0127)	(0.0320)
$InflationSVI_{i,t-2} \times Shadow_{i,t-2} \times Darknet_{t-2}$		0.0090	−0.0031	0.0319
		(0.0067)	(0.0132)	(0.0322)
$InflationSVI_{i,t-3} \times Shadow_{i,t-3} \times Darknet_{t-3}$		0.0065	0.0244	−0.0357
		(0.0135)	(0.0161)	(0.0254)
Observations	2,753	2,753	1,516	1,237
Countries	28	28	14	14
R^2	0.0848	0.1024	0.0379	0.0691

Each specification is a fixed effects regression, estimated using the total sample and for countries with either above or below median annual inflation over the sample period. Controls include time fixed effects, the natural log of national Google search intensity for the term "Bitcoin" in country *i*, the total weekly return on country *i*'s benchmark stock index, the change in the natural log of weekly turnover for country *i*'s benchmark stock index, the natural log of volatility for country *i*'s benchmark stock index during the last ten trading days, the change in the natural log of median weekly market capitalization for country *i*'s benchmark stock index, country *i*'s annual inflation rate, and the natural log of country *i*'s real GDP per capita. Standard errors are clustered at the country level. (***) denotes significance at the 1% level, (**) at the 5% level, (*) at the 10% level.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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