Making Money*

Gary B. Gorton[†] Chase P. Ross[‡] Sharon Y. Ross[§]

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Abstract

It is difficult for private agents to produce money that circulates at par with no questions asked. We study two cases of privately-produced money: pre-Civil War U.S. private banknotes and modern stablecoins. Private monies are introduced when there are no better alternatives, but they initially carry an *inconvenience* yield. Over time, these monies may become more money-like, but they do not always achieve a positive convenience yield. Technology advances and reputation formation pushed private banknotes toward a positive convenience yield. We show that the same forces are at work for stablecoins.

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[†]Yale University & NBER. Email `gary.gorton@yale.edu`

[‡]Board of Governors of the Federal Reserve System. Email: `chase.p.ross@frb.gov`

[§]Office of Financial Research, U.S. Treasury. Email: `sharon.ross@ofr.treasury.gov`

> Everyone can create money; the problem is to get it accepted.
>
> (Minsky, 1986)

1 Introduction

The growth of stablecoins raises the question of how private agents can produce money. We study two types of debt as their issuers try to make them money-like: pre-Civil War private banknotes and modern digital stablecoins. The birth of new privately-produced money requires two ingredients: a lack of alternatives and a design that makes the money acceptable at par with no questions asked (NQA). We show that technology advances and reputation formation push privately-produced monies toward positive convenience yields—first for private banknotes, then for stablecoins.

Different forms of private debt can transition from non-money to money, but the transition is neither immediate nor smooth. In the language of Holmström (2015), debt is money only if agents accept it NQA: they must accept the debt at par without reservation or costly due diligence. NQA money is an economy's bedrock. Without it, transactions are inefficient, consuming resources and time. NQA money protects uninformed agents from adverse selection because it is information insensitive (Gorton and Pennacchi, 1990). But many forms of debt, even with the shortest maturities and highest credit ratings, do not trade no-questions-asked: money is special. It has a convenience yield because of the nonpecuniary benefits of being NQA.[1]

We present a model which focuses on a variable designed to capture a money's distance from NQA, which we call d. d is a continuous, nonnegative, latent variable that summarizes the frictions that prevent debt from becoming NQA. Making money involves decreasing d. The interpretation of d changes depending on the institutional context. The variable d summarizes the forces that create a money's convenience yield. When the distance to NQA is zero, $d = 0$, the debt trades NQA and is information insensitive. Even if $d > 0$, we show a money can still have a positive convenience yield. Questions are asked about the money's

[1] The convenience yield is the yield spread between a money-like security and a benchmark security, where the only difference is that one is money-like. For example, a measure of the Treasury convenience yield compares the spread between overnight-indexed swaps (OIS) and Treasury bills of the same maturity. OIS are nearly riskless derivatives, but Treasuries are more money-like than OIS because institutional investors can spend Treasury bills like money. Other potential benchmark measures include the general collateral finance repo rate or high-quality corporate bond yields (Krishnamurthy and Vissing-Jørgensen, 2012).

backing, but it can have a positive convenience yield. But as d grows larger, the convenience yield flips signs and becomes an *in*convenience yield. Our empirical results show stablecoins are following the well-trodden path to NQA but remain in their early days.

Before the U.S. Civil War, banks issued non-interest-bearing debt in the form of banknotes. There were about 1,500 distinct banknotes in the mid-1840s. Depositors could redeem banknotes in specie at par on demand, but only at the specific bank that issued the note. Different banknotes traded at different discounts from par (Gorton, 1999). In the pre-Civil War Free Banking Era, from 1834 to 1863, some states allowed free banking—easy entry into banking—but required banks to back their banknotes with state bonds, with the requirements varying across states. In other states, banks issued banknotes backed by loan portfolios.

The distance to NQA d takes an almost literal interpretation of physical distance to the issuer for private banknotes. Banknotes circulating in the city of the issuer were treated as money, no-questions-asked. Banknotes from distant cities traded at a greater discount, reflecting that questions were asked. But redeeming banknotes from distant banks was costly in time and money. Over time, d decreased with the proliferation of technology like railroads and telegraphs.

Railroads reduced d as travel times plummeted during the nineteenth century (Gorton 1989, Atack et al. 2015, and Lin et al. 2021). The expansion of the telegraph followed new railroad lines, allowing information to move faster. A trip from Philadelphia to Memphis in 1839 covered more than 1,650 miles spanning five connections on steamboats and stagecoaches. The trip took more than 13 days and cost \$70 (\$1,780 in 2021). By 1862, the same trip took three and a half days and cost \$45 (\$800 in 2021) thanks to the burgeoning railroad network. In only 23 years, the real cost fell 55%, and the travel time fell 73%.

Stablecoins are the newest form of privately-produced money to attempt the money transition. The largest cryptocurrencies are too volatile to be stores of value or transaction media, and there are significant opportunity costs to holding dollars inside a crypto exchange. Stablecoins emerged to fill the gap. Stablecoin issuers solve the volatility problem by pegging the coin to safe assets one-for-one; the pegs are often sovereign currencies like the U.S. dollar or the euro. The peg does not always hold, though, and stablecoins occasionally break their peg. A broken peg can lead to the outright failure of the stablecoin, the cryptocurrency equivalent to a bank run.

For stablecoins, d is a latent variable that reflects a trader's frictions in transacting and in redeeming the stablecoin to a sovereign currency. Stablecoin holders face many frictions: the time it takes to satisfy anti-money laundering and Know-Your-Customer laws when transferring balances between stablecoins on crypto exchanges and bank accounts; the inability of citizens of certain countries to redeem the coins from the issuer; transaction limits that make redemption of small amounts of stablecoins to dollars impractical. d decreases as frictions decline. We show that technological change in the form of faster graphics processing units reduces stablecoins' d.

We estimate d for both private banknotes and stablecoins following Gorton (1999)'s stylized model. Private banknotes and stablecoins are non-interest-bearing perpetuities with embedded put options to redeem at par from the issuer, so Black and Scholes (1973) holds. Gorton (1999) identified the put option maturity as the time it took to travel to the issuing bank. He used the model to back-out banknotes' implied volatilities and that they were related to state-level risk factors. In our application, we back-out d as the maturity of the banknote or stablecoin implied by prices. The model also shows how d is negatively related to the convenience yield of the money.

d is endogenous, and issuers try to reduce it. Issuers use their reputation as a technology to reduce d. Agents are more likely to trust reputable issuers with a history of redemption at par, while agents carefully monitor issuers with less reputation. Gorton (1996) shows that notes issued by new private banks traded at a discount to those of seasoned banks at the same location, giving traders an incentive to redeem the notes and implicitly monitor the new bank's ability to repay. Stablecoin issuers can improve their reputation and endogenously decrease d by disclosing details about the assets backing the stablecoin, getting a fintech banking charter, or appointing well-known people to their boards. Over time, either through technological change or through the issuer's efforts—or both—d can fall. The convenience yield goes up, and the debt becomes money, possibly with a positive convenience yield, even if d is always greater than zero.

Despite issuers' best efforts, d does not follow a steady path toward zero. Our estimates of d for both banknotes and stablecoins are countercyclical. Recessions and financial crises in the nineteenth century are apparent in the d time series. Large drops in Bitcoin's price, the closest proxy we have to a recession indicator in cryptocurrencies, similarly correspond to large increases in stablecoins' d.

We have four main results: first, we estimate d for banknotes and stablecoins and study their dynamics. We show that d can shrink over time, but not uniformly. Second, we measure both banknotes' and stablecoins' convenience yields—or, when negative, their inconvenience yields—and show that d is negatively correlated with the convenience yield. Third, we show that technological change and reputation development reduce d. But, fourth, stablecoins have not differentiated themselves from other stablecoins. The market essentially views stablecoins as a single coin, making them more vulnerable to runs since all stablecoins face large volume drops during stress.

Related Literature Our paper is most related to the quickly growing literature on stablecoins and is closely related to Gorton and Zhang (2021). Mizrach (2021) provides a detailed description of the market microstructure of stablecoins and studies their failure rates. Lyons and Viswanath-Natraj (2021) frame stablecoins in the light of exchange rates and show that Tether's peg is maintained primarily by the demand side, arbitrageurs, rather than the supply side, the issuer. They also show how the premium or discount relative to the peg varies over time. Hoang and Baur (2021) show how stablecoins' volatility is closely linked to Bitcoin. Other studies include Bellia and Schich (2020), Cao et al. (2021) and Kwon et al. (2021).

2 Estimating the Distance to No-Questions-Asked

We use Gorton (1999)'s model for a simple conceptual framework to link the prices of different types of monies to their distances from Holmström (2015)'s no-questions-asked. Private banknotes and stablecoins are non-interest-bearing perpetual debt with embedded put options for redemptions at par on demand from the issuer. Gorton (1999) applied a pricing model, discussed below, to private banknotes, which we use to describe stablecoins. We provide a brief sketch of the model setup to motivate the main result, with which we estimate d.

Agents are spatially separated, and each agent comprises a household, firm, and a bank. The distance from the agent's home market to the location of their trade in a period is d. Each household owns a firm that produces a nonstorable stochastic endowment in each period. The households issue debt and equity claims on their endowment streams. The debt pays no interest and is redeemable into consumption goods on demand at par. The debt, therefore, is equivalent to a perpetuity with an embedded American put option.

The household comprises a buyer who travels to a distant market to buy goods and a seller who stays at home to sell their firm's endowment. Households face a cash-in-advance constraint that can be satisfied only by banknotes:

$$C_t \leq \sum_d P_t(d) D_{t-1}(d) \tag{1}$$

where $P_t(d)$ is the price at time t of a note issued by household with distance d away and $D_{t-1}(d)$ is the household's holdings at the beginning of period t carried over from period $t-1$. From period to period, households hold a portfolio of banknotes issued by other households at different locations with different ds. The households pay for consumption goods at distant locations with their portfolio of banknotes.

Households prefer to consume goods from markets far away from their home location. Households' preference for goods from distant markets can be motivated by the pre-Civil War division of labor. Households maximize expected utility

$$\mathbb{E}_t \left[\sum_{j=t}^{\infty} \beta^{j-t} u(C, d) \right] \tag{2}$$

Households also have the choice to send banknotes for redemption. By assumption, a banknote with price $P_t(d)$ takes d periods to be redeemed at face value in consumption goods $P_{t+d}(0) = 1$, assuming the bank is solvent. The household's first-order condition with respect to their banknote portfolio pins down the price of a banknote:

$$P_t(d) = \mathbb{E}_t \left[\beta^d \frac{u'_{C,t+d}}{u'_{C,t}} P_{t+d}(0) \right] \tag{3}$$

where $\mathbb{E}_t$ is the expectations operator conditional on information available at date t.

The first-order condition shows that banknotes of a bank with distance d are equal to risky pure discount debt with a maturity of d periods.[2] Households must be indifferent between holding a banknote and sending it for redemption.

We can back out the money's maturity given the price of the debt and a standard option pricing method. Let $D_t^R(d)$ be the face value of debt sent for redemption at date t from

[2]See Gorton (1999)'s Proposition 1.

location d and assume there are no notes in transit. Given the price of the banknote,[3] we can back out d using Black and Scholes (1973):[4]

$$P_t(d) = \frac{V_t(d)[1 - N(h_D + \sigma)] + (1 + r_f)^{-1} D_t^R(d) N(h_D)}{D_t^R(d)} \tag{4}$$

where

$$h_D \equiv \frac{\ln(V_t(d)/D_t^R(d)) + \ln(1 + r_f)}{\sigma} - \frac{\sigma}{2}$$

and σ is the standard deviation of one plus the rate of change of the value of liability issuer, r_f is the risk-free rate, $V_t(d)$ is the value of the debt and equity claims on the issuer, and $N(\cdot)$ is the cumulative normal distribution function.

We make two simple additions to the model to study the convenience yield. First, the banknote yield is the inverse of its price: $R_t^d = 1/P_t(d)$. Second, we derive the risk-free rate from the stochastic discount factor even though the model has no risk-free security. The risk-free bond price is pinned down by $1 = \mathbb{E}_t \left[M_{t+1} R_t^f \right]$ where M_{t+1} is the stochastic discount factor. The convenience yield is the difference between the yields on the risk-free bond and the debt:

$$\text{Convenience Yield}_t \equiv R_t^f - R_t^d \tag{5}$$

Proposition 1. *If $D_t^R(d)V_t'(d) - D_t^{R'}(d)V_t(d) < 0$, then the convenience yield is decreasing in d: $(\partial(CY)/\partial d) < 0$. We provide the proof in Appendix A.1.*

For intuition on our assumption that $D_t^R(d)V_t'(d) - D_t^{R'}(d)V_t(d) < 0$, we first note that the bank value is the sum of its debt and equity: $V_t(d) = D_t^R(d) + E_t(d)$. Then the leverage ratio is

$$\frac{V_t(d)}{E_t(d)} = \frac{D_t^R(d) + E_t(d)}{E_t(d)} = \frac{D_t^R(d)}{E_t(d)} + 1.$$

Empirically, the leverage ratio for banknotes is about two, so the average bank's debt and equity are about equal, $D_t^R(d) \approx E_t(d)$. After we substitute the equations $V_t(d) = D_t^R(d) +$

[3] Banknote prices were publicly reported in banknote reporters, which we discuss in section 3.
[4] See Gorton (1999)'s Proposition 2 and Rubinstein (1976).

$E_t(d)$ and $D_t^R(d) \approx E_t(d)$, then $D_t^R(d)V_t'(d) - D_t^{R'}(d)V_t(d)$ simplifies to $E_t(d)(E_t'(d) - D_t^{R'}(d))$. If $E_t'(d) < D_t^{R'}(d)$, then $(\partial(CY)/\partial d) < 0$.

Both $E_t'(d)$ and $D_t^{R'}(d)$ are negative. Debt is senior to equity, so equity is more information sensitive and $E_t'(d) < D_t^{R'}(d)$. For example, bank stock prices are magnitudes more volatile than senior bank debt prices.

For banknotes, $D_t^R(d)$ is stickier than $E_t(d)$. Concerns about the market value of the bank would lead $E_t(d)$ to fluctuate quickly, but $D_t^R(d)$ would take longer to adjust because it would take time to deliver bad news about a bank's circulating notes and to have the new discount reflected correctly in the banknote reporter.

Observations First, a banknote does not have to satisfy NQA to carry a positive convenience yield. We denote $d^\star$ as the distance at which the convenience yield equals 0. If $d < d^\star$ then the convenience yield is positive; if $d > d^\star$ the convenience yield is negative—it will carry an inconvenience yield. A credible government can produce NQA money ($d = 0$) which earns the largest possible convenience yield. Even if the government is the only issuer that can produce genuinely NQA money, private issuers can still produce money that earns a positive convenience yield if the money is close enough to NQA, $d < d^\star$. There is a direct link between the distance to NQA and the convenience yield.[5]

Second, the debt price is \$1 when $d = 0$, $P_t(0) = 1$. When $d = 0$, the debt can be redeemed immediately, so an agent must be indifferent between holding it at \$1 or redeeming it for \$1 so long as the bank is solvent. When $d = 0$, there are no-questions-asked, and all agents accept the debt at par value as money.

Third, the debt price $P_t(d)$ is inversely related to distance to NQA d, the volatility of the issuer's debt and equity σ, and the issuer's leverage. When the distance to NQA d increases, the debt price falls.

Gorton (1999) used the model to back out implied volatilities and then analyzed them in cross-sections to show their relationship to state-level risk factors. In that analysis, maturity was taken as the time to return to the issuing bank computed from historical travel data. In our analysis for banknotes and stablecoins, we use historical data for volatility and back out d. This distance to NQA is affected by all the variables in equation 4.

[5]We plot R_t^d and R_t^f on the left panel of Figure A1 and the convenience yield on the right panel.

3 Pre-Civil War Private Banknotes

We briefly provide some background on the use, trading, and evolution of Pre-Civil War private banknotes from roughly 1820 to 1860.[6] We verify our estimation strategy for d and show that the estimated distance to NQA aligns closely with physical distance. We also show the decline in the distance to NQA d and the inconvenience yield over time.

3.1 Context

Private banknotes were physical currency issued by a specific bank redeemable into specie, at par, on demand. Private banknotes were liabilities issued by the bank to finance bank loans. Banks began issuing notes before the nineteenth century, but the number of unique banks issuing notes grew substantially in the nineteenth century (Gouge, 1833). Our interest is primarily the *Free Banking* period from 1837 to 1863, when banks issued private money backed by state bonds. The bonds were not riskless, and banking panics were common.

The Free Banking period was so-called because there was free entry into banking after eighteen states passed laws that allowed banks to issue private money backed by state bonds. The remaining fifteen states retained a framework that required a charter before a bank could open and issue notes. Getting a bank charter did not require tremendous effort in Free Banking states. Someone could open a bank by purchasing state bonds, depositing those bonds with the state government, and printing private banknotes for circulation. The banks had limited liability, but the state would revoke its charter if it could not redeem its notes on demand. Rolnick and Weber (1984) and Gorton (1996) study the existence of, or lack thereof, *wildcat* banks: banks opened by fraudsters for the sole purpose of issuing worthless paper money and absconding with the proceeds.

Money in the Free Banking period was not economically efficient. It was costly to use specie because it was heavy and difficult to transport in large amounts. Coins were also scarce. The available coins came in a confusing array of denominations. "In routine business transactions Americans had to calculate in three currencies: one decimal; another based on halves, quarters, and eighths; and another on twelfths and twentieths" (Ware, 1990). The

[6] See Gorton (1996), Rolnick and Weber (1984), and Gorton (1999) for discussions of nineteenth-century bank money.

U.S. Mint could not remint foreign coins because of poor minting equipment (Carothers, 1930). Consequently, private banknotes played a vital role in commerce.

The public carried notes from a hodgepodge of banks in their pocket for everyday transactions. Merchants and customers feared counterfeits and notes issued by dead or dying banks. It was hard to tell the good notes from the bad—especially for notes issued by unfamiliar distant banks. Merchants preferred notes with noticeable wear-and-tear, evidence of robust circulation where other merchants had accepted it. Merchants would accept notes issued by distant banks only at a discount to par: the further away the bank, the greater the discount.

Discount note brokers traded private notes on secondary markets in New York, Philadelphia, Cincinnati, and Cleveland. Risky banks' notes traded at a bigger discount than safer banks' notes, ceteris paribus. Banknote discounts varied over time, spiked during crises, and tended to be small.

Banknote reporters summarized information produced by the secondary markets.[7] (We discuss the data in greater detail below.) Banknote reporters were regularly updated lists of banks and their corresponding discounts which merchants referenced for routine commerce. Scroggs (1924) describes this as follows:

> Hundreds of banknotes of different size, colour, and design would be handed across the merchant's counters every day. If he were in any doubt about the value of a note, he would turn to his banknote detector. Most detectors described the distinguishing characteristics of more than a thousand bank issues. Details were also given of any counterfeits or alterations, or of recently discovered issues of fictitious banks ... If the note were unfamiliar the merchant would spend some time checking its description with that given in the detector. One can scarcely imagine a customer in a store today waiting patiently while each bill that he had offered was carefully examined before being accepted.

People spent tremendous resources to avoid lemon notes, yet bank failures and financial crises were common. Even if the brokers' discount markets were efficient, pre-Civil War notes were economically inefficient forms of money because they had a considerable distance to NQA (Dow and Gorton, 1997).

[7] As an example, Figure A2 plots the discounts for two select banks over time: the Bank of Montgomery County and the Farmers' Bank of Virginia.

The Free Banking period ended when the National Banking period began in 1863 after the U.S. government allowed banks to issue national banknotes backed by U.S. Treasuries. The government initially created the system to help finance the government's Civil War efforts, but many believed that backing paper money with U.S. Treasuries would bolster financial stability.[8]

Data We use three data sources for private banknotes: banknote quotes from Weber (2021), bank balance sheet data from Weber (2018b), and railroad location data from Atack (2016).

Discounts reflect the cost to buy a bank's notes with specie. The quoted discounts on state banknotes are available on select dates between 1817 and 1858. Weber (2021) gives banknote prices, expressed as discounts from par, at secondary markets in New York, Philadelphia, Cincinnati, and Cleveland. Quotes come from two datasets based on the quote's location: Philadelphia or New York/Ohio. The New York/Ohio[9] dataset has a longer time series, but the Philadelphia data has more observations in the 1850s. Many banknotes appear to have traded in both locations. Weber (2018a) provides a comprehensive description of the data. We summarize the sources and timeframes in section A.2.

Weber (2018b) collects bank balance sheets by state from many sources with data back to 1794. Weber (2018b) cleans and regularizes the data to consistent asset and liability categories. We merge the balance sheet data to the pricing data by lagging the end-of-year balance sheet data by one year to avoid using future data.[10]

We merge the balance sheet data with banknote discount data by first checking banks in states with exact matches across the datasets, then fuzzy matching on their names and manually checking the matches. We then collapse the data to the month by bank by dataset level by averaging within a month. Our resulting dataset includes about 230,000 quotes for 1,750 individual banks from 30 states—including 80,000 New York/Ohio-based quotes and 150,000 Philadelphia-based quotes.[11] Since several banks appear in both datasets, we run regressions on each dataset separately to prevent double-counting.

[8] Noyes (1910), Friedman and Schwartz (1963), and Champ (2007) discuss the National Banking period.

[9] We will refer to this dataset as the *New York dataset* for brevity and because it is principally composed of quotes from New York.

[10] Figure A3 plots the number of banknotes in our sample for each month from 1817 to 1860.

[11] The data includes banknotes for some institutions that were not banks; we include these because the fact that detectors collected the data is prima facie evidence that the notes were money-like.

In our data, the quotes range from 0 to 90.[12] A banknote with a discount of 0 has a price of $1. A quote of 90 means it costs $0.10 to buy $1 face value of banknotes, and the bank is likely bankrupt. The mean quote is 1.5%, and the median is 0.5%. Gorton (1996) describes banks with quotes greater than the modal quote for that state as likely bankrupt. Quotes are available for both healthy and unhealthy notes, and there is considerable cross-sectional heterogeneity: the within-month standard deviation across quotes is 6.6% in New York and 3.6% in Philadelphia.

Atack (2016) provides the location of railroads through the nineteenth and early twentieth century, described in Atack (2021). The data uses historical and U.S. Geological Survey topographic maps to trace transportation infrastructure and provide the first year the railroad segment began operating.

We are interested in the railroad network that connects to Philadelphia. We define Philadelphia railroads as those that pass within five miles of the center of Philadelphia. We then define the Philadelphia railroad network as all the railroad segments that pass within five miles of another railroad that itself passes within five miles of Philadelphia. Iterating the logic many times traces the Philadelphia railroad network by year.

We also find the location of each bank in the Weber (2021) using OpenCage Geocoding. Since we do not know the exact bank addresses, we use the location returned by the OpenCage Geocoding API, normally the town center.[13]

We use the Moody's Municipal Bond 20-year Composite Yield, the Moody's Corporate AAA Bond Yield, and the 10-Year Treasury yield from Global Financial Data.[14] We use historical travel times collected by Gorton (1989). We also use crisis dating from Trebesch et al. (2021).

[12] During the Panics of 1839 and 1857, some banks suspended the convertibility of notes to specie. The banknote reporter changed the quote numeraire from specie to Philadelphia banknotes. As a result, there are many negative quotes, as much as -15%, indicating that the specific banknote was more desirable than the Philadelphia banknotes with which you could buy it (Gorton, 1996).

[13] We exclude banks with no cities given. For banks with multiple towns listed, e.g., "Beaver Dam/Lodi, Wisconsin", we use the first listed city. We also manually clean several town names for mispellings or small differences with modern names, and if we cannot find a modern town in the same area, we match it to a nearby town.

[14] The AAA corporate bond series uses individual corporate bonds before 1857. A true AAA corporate bond series doesn't exist for this period. The municipal bond yield also uses individual bonds from different states between 1789 and 1856. At the time, municipal bonds were considered safe assets. The municipal index is primarily composed of New York and Massachusetts municipal debt. Appendix section A.2 gives details on the underlying bonds used in the indices.

3.2 Empirical Results

We present our empirical results in three steps: first, we describe how we estimate the distance to NQA d, and describe its evolution. d is positively correlated with measures of technological change in transportation and implicitly information since telegraphs were strung along train lines. With the telegraph, agents could receive information about a bank faster, and the increased spread of information would affect σ and hence d. Second, we describe our convenience yield measures and their dynamics over time. Finally, we use instrumental variables to show the relationship between transportation technology and banknotes' convenience yields.

Distance to No-Questions-Asked Let d_{it} represent the true distance to NQA for bank i at time t. We estimate the distance to NQA, denoted $\hat{d}_{it}$, using the option pricing expression in equation 4. We convert discount quotes to prices for bank i at time t using

$$P_{it} = 100 - \text{Quote}_{it}.$$

We make four assumptions to estimate $\hat{d}_{it}$. First, we assume that the firm's value $V_t(d)$ is the value of the bank's assets. Second, we assume \$1 of notes is sent for redemption, $D_t^R(d) = 1$. Third, we estimate volatility σ using the annualized standard deviation of the bank's monthly asset growth over the previous twelve months; we require the data have at least three months of asset growth. Fourth, we use the 10-Year Treasury yield series compiled by Global Financial Data as the risk-free rate.

We exclude banks without data on quotes or total assets, including banks with total assets reported as zero. To measure the economy-wide $\hat{d}_t$, we calculate a weighted average of individual bank-month $\hat{d}_{it}$ estimates using the lagged market value of the bank's circulation, which we calculate as the previous year's circulation balance sheet item multiplied by the previous month's quote price. We use circulation as a weighting variable since banks with more banknotes in circulation were likely more important for aggregate $\hat{d}_t$ dynamics. We also drop $\hat{d}_{it}$ estimates when a quote is negative during the Panics of 1839 and 1857.[15]

[15] Alternatively, we also estimated $\hat{d}_{it}$ where $P_{it} = 100/(100 - \text{Quote}_{it})$, which essentially flips the trade: buy the more desirable banknote outside of Philadelphia and sell it in Philadelphia for a premium. We use this logic to estimate stablecoins' $\hat{d}_{it}$ since for stablecoins $P_{it} > 1$ regularly. Using this alternate trade for

In Figure 1, we plot the economy-wide $\hat{d}_t$ over time. Over the full sample, the average $\hat{d}_t$ for New York quotes is 0.88 years and 0.30 years for Philadelphia quotes. $\hat{d}_t$ has a clear downward trend and a separate cyclical component. Given the tremendous technological progress over these four decades, we expect that $\hat{d}_t$ falls as banknotes move closer to NQA. Regressing $\hat{d}_t$ on a time trend captures this intuition: each year $\hat{d}_t$ decreased 21 days for New York quotes and 4 days for Philadelphia quotes, and both trend coefficients are statistically significant.

To confirm that our $\hat{d}_t$ estimates are robust, we perform the estimation using several different assumptions regarding the risk-free rate and volatility σ. We report the results from these alternative specifications in Table A1. First, we try alternative risk-free rates, including a series of commercial paper yields from Global Financial Data collected by Smith and Lole (1935), which uses data first provided in Bigelow (1862). The data reflects "'street rates' on first class paper in Boston and New York" and spans 1836 to 1862. During the period, the commercial paper yield averaged 9.2% and the Treasury yield index averaged 5.3%. The two series do not appear closely correlated. The $\hat{d}_t$ estimation is not sensitive to the choice between these two risk-free rates given the large returns implied by the discount on banknotes. Second, we estimate $\hat{d}_t$ using a fixed risk-free rate of 5% and 9%. Third, we use volatility in the monthly price return of the banknote over the previous year instead of using the volatility in the monthly asset growth over the previous year. Across all alternative estimations, the results are broadly consistent and highly correlated with our main estimation.

d takes an almost literal interpretation in the pre-Civil War period: a banknote is risky debt with a maturity equal to the time to take the note from the central market—often Philadelphia—to the issuing bank. The actual travel time and d estimates should line up if banknotes are priced efficiently. We report the correlation of $\hat{d}_{it}$ with a handful of other variables in Table 1. The first two columns show that our estimated $\hat{d}_{it}$ is positively correlated with actual travel distance and cost as compiled by Gorton (1989) using historical travel guides. The correlations in the first two columns include banks in cities with travel data and in years with quotes in Philadelphia since our travel data is relative to Philadelphia.[16] We use the median quote of a bank in a year since we do not know which month of the year the

banknotes does not materially affect our results because only a small share of the quotes in our sample are negative and only during the Panics of 1839 and 1857.

[16]Since we have no quote data in 1862, we match the travel data from that year to 1858 quotes.

travel data was compiled and to reduce the influence of outliers. This result confirms that our methodology for estimating $\hat{d}_{it}$ aligns the estimated distance with the true distance to NQA d_{it}. Further, it shows that declines in $\hat{d}_{it}$ are associated with transportation technology advances.

The remaining columns in the table are also as expected: $\hat{d}_{it}$ is lower over time and as banks age. $\hat{d}_{it}$ is unsurprisingly higher during crises. $\hat{d}_{it}$ is also lower in Free Banking states, which might be surprising but is consistent with Gorton (1999)'s discussion that it is not obvious if Free Banking was riskier than states with traditional charters.

One concern is that survivorship bias affects the interpretation of our results. Banknote detectors did not generally provide quotes for the notes of bankrupt banks or otherwise quoted them as *uncertain*. Our results do not say that simply surviving lowers d. Banks that survived were precisely those able to lower their d by developing a reputation even as technology proliferated, making bank monitoring easier.

Convenience Yield We measure the convenience yield as the spread between high-quality corporate bonds and the implied yield on bank i's banknote at time t using the note's discount:

$$\text{Convenience Yield}_{it} = \text{Benchmark Yield}_{i,t-1} - \left(\frac{\text{Banknote Quote}_{it}}{100 - \text{Banknote Quote}_{it}}\right) \tag{6}$$

We calculate the banknotes' implied yield using the note's discount. The expression for a banknote's yield reflects what a note broker would earn by taking the note to the issuing bank and redeeming it at par in specie.[17]

Our benchmark yield measure is Moody's corporate bond index from Global Financial Data, and for robustness we confirm results are consistent when using Moody's Municipal Bond 20-year Composite Yield. We use the two bond indices to compute a counterfactual: if there were such a form of AAA-rated money, how would its yield compare to the yields on private banknotes? We lag the benchmark yield by one month to avoid comparing banknote yields with future benchmark yields since quotes are often in the middle of the month.

[17] The expression assumes that brokers take notes back to the issuing bank once a year. This is most conservative assumption since taking notes back more frequently would raise a note's annualized yield.

Suppose a \$1 banknote issued by a bank in the Nebraska territory traded for \$0.90 in Philadelphia. A trader could potentially earn a yield on that banknote by buying it in Philadelphia, traveling to the Nebraska bank, and redeeming the note for \$1 of specie, giving a yield of 11% ($1/0.9 \approx 1.11$). The second term in equation 6 captures the logic of this trade.[18]

We plot the value-weighted pre-Civil War convenience yield in Figure 2. In the first decade of our data from 1817 to 1826, our benchmark measure of the convenience yield averages −4.8% but with a distinct upward trend: over the period 1817 to 1858 the convenience yield increases roughly 0.27 percentage points (pp) each year using New York quotes. The upward trend remains if we remove the first volatile decade: limiting to data in 1830 and later, the convenience yield increased roughly 0.13pp per year with New York data and 0.09pp with Philadelphia data. The convenience yield of banknotes also falls during crises: the convenience yield is 4.2pp lower during banking crises and regularly turns negative.

Table 2 describes the summary statistics of the value-weighted pre-Civil War convenience yields. The full sample convenience yield is 2.1% using New York quotes and the corporate bond benchmark and 1.0% using the municipal bond benchmark. Since the Philadelphia quote data begins in the 1830s, the apples-to-apples comparison of the New York-based and Philadelphia-based convenience yields is the post-1835 rows: 4.2% for New York and 4.8% for Philadelphia.

We argue that banknotes became more convenient to use as money over this period, evidenced by the larger convenience yield in the post-1835 sample (4.2%) than the full sample (2.1%). The effect is not driven by benchmark yields increasing; in absolute terms, aggregate New York banknote yields fall from 5.2% before 1835 to 2.7% after.

Banknotes must decrease their distance to NQA to be more convenient. We test the logic by regressing the convenience yield on the physical distance to the bank, d_{it}. Table 3 presents the regression results, where we regress bank i's convenience yield at time t on the travel time

[18] The implied returns on banknotes are high enough that including estimates of travel costs and travel times—e.g., subtracting travel costs from the \$1 payoff and assuming the broker can continuously take round trips from Philadelphia to the city—makes the estimated banknote yields even larger. We prefer our simpler measure because the trade profits, including travel costs and times, are sensitive to what share of a bank's circulation the broker can get in the market; the more notes the broker can redeem, the more they can wash out fixed travel costs. Banknote detectors did not report volume data, so we cannot know what volume of banknotes a broker could realistically buy at the secondary market. Moreover, because notes varied in size and shape, there are likely weight limitations about which we can only speculate.

from Philadelphia to the bank's city in days. There is a strong negative relationship between the convenience yield and d_{it}: the farther away the bank, the smaller its convenience yield. The convenience yield falls by 0.26pp for each extra day it takes to travel from Philadelphia to the bank using the corporate bond convenience yield (column 1). The estimate is similar using the municipal bond convenience yield, which decreases by 0.21pp for each extra day (column 5). The remaining columns show that the strong negative relationship between the two variables is robust to including year and bank fixed effects.

The results in the table also give insight into $d^\star$: the distance at which the banknote switches from earning a convenience yield to earning an *inconvenience* yield. Any banknote with a distance to no-questions-asked $d_{it} < d_t^\star$ will have a positive convenience yield, and any banknote with $d_{it} > d_t^\star$ will have a negative convenience yield—an inconvenience yield. We can back out the average $d^\star$ by comparing the regression constant with the d_{it} coefficient. Using column 1, $d^\star$ is about 23 days ($6.05/0.26 = 23.3$).

Relationship Between Distance to No-Questions-Asked and the Convenience Yield Next, we use an instrumental variables strategy to show the effect of d on the convenience yield. We exploit banks' distances to the East Coast railroad network to show that d and the convenience yield have a negative relationship, consistent with Proposition 1.

Railroads were built to connect major cities, with some of the first railroads built in the 1800s to connect New York and Philadelphia. Our empirical approach focuses on what we call the *low-cost* line. The shortest distance—and cheapest route to build—between two towns is a straight line. We construct the low-cost line as the straight line that connects Boston, New York City, Philadelphia, Washington, D.C., and Wilmington in the spirit of Berger and Enflo (2017). We also include three other towns (Stamford, CT; Baltimore, MD; and Fredericksburg, VA) to avoid major bodies of water.

Figure 3 shows the railroad network built by 1849, the towns with banks, and the low-cost line. Our key identifying assumption is that banks between the major cities exogenously gained access to the rail network because of their location—they happened to be near the low-cost line. Total railroad miles grew rapidly beginning in 1850, and the rail network grew endogenously to connect many towns throughout the East Coast and the Midwest. Thus, we restrict our analysis to before 1850. We also exclude banks located in the five main cities since railroads were endogenously constructed to connect those cities.

Our primary instrument is the bank's distance to the low-cost line. In the first-stage regression, we use the distance to the low-cost line to predict d_{it}. We use three measures of physical distance d_{it}—time to Philadelphia, cost to travel to Philadelphia, and distance to the Philadelphia railroad network.[19] We regress the convenience yield on the predicted distances while controlling for the bank's assets, leverage, and circulation in the second-stage regression.

Table 4 shows the results.[20] Panel A shows the second-stage result. Columns 1 and 2 show that the convenience yield declines by nearly 1pp for five additional days of travel to Philadelphia or an additional $34 to travel to Philadelphia. Column 3 shows that banks further from the Philadelphia railroad network also have lower convenience yields. The instrumented regression gives similar coefficients to the OLS regression in Panel C.

In columns 4 to 6, we also show the second-stage result if we estimate the d variables using an indicator variable for whether a bank is within 30 miles of the low-cost line, an estimate for how far someone can travel in a day. The regression in Panel B shows that being within 30 miles of the low-cost line reduces the travel time by a day. These results are robust to changing the cutoff. In Panel A, the larger coefficients when using the indicator variable suggest that the convenience yield declines by around 1pp for two additional days of travel or an additional $16 to travel to Philadelphia.

Panel B shows the first-stage regression results. The instruments satisfy the relevance condition, and the F-statistics indicate the instruments are strong. Appendix A.3 discusses the exclusion restriction and falsification tests.

4 Stablecoins

Stablecoins are privately-issued digital tokens on a blockchain. Issuers purport to back their stablecoins one-for-one with reserves, an effort to approximate NQA status. We first provide background on stablecoins' use, trading, and recent evolution. Then we turn to the data and empirical results to show the dynamics of d and the inconvenience yield over time.

[19] Time and cost to Philadelphia are exact for cities with data in Gorton (1989) and estimated for other cities by regressing the actual time and cost data from Gorton (1989) on the driving miles between Philadelphia and that town using Google Maps.

[20] The table shows the results using corporate bond convenience yield, but results are similar using the municipal bond convenience yield.

4.1 Context

Stablecoins are the second generation of cryptocurrencies, following fiat cryptocurrencies like Bitcoin. The first generation has volatile prices. Stablecoin prices should not be as volatile as fiat crypto coins since they are purportedly backed one-for-one with reserves. Gorton and Zhang (2021) argue that stablecoin issuers are essentially banks because the terms of service say traders can usually redeem a stablecoin for one U.S. dollar. In other words, an agent deposits one U.S. dollar and receives one dollar of the coin, which the agent can redeem back to U.S. dollars. There are hundreds, if not thousands, of stablecoins, but the top five account for 95% of the market.

The most common current uses of stablecoins involve cryptocurrency trading. Investors convert fiat currency into stablecoins and using those stablecoins to buy and sell other crypto tokens. Agents can use stablecoins to exit volatile cryptocurrency positions without entirely exiting a crypto exchange and redeeming to U.S. dollars, which can involve material transaction costs. Agents often lend stablecoins to earn interest from borrowers who want leverage to buy other cryptocurrencies. The largest stablecoins do not pay interest, and—ideally—their prices are fixed, so a stablecoin's pecuniary return comes entirely from lending to borrowers who want leverage.

Ease of redemption varies across stablecoins. Stablecoins cannot be used off-chain to buy groceries, for example. And different blockchains are not interoperable, so they are difficult to move from one blockchain to another: the different blockchains can't talk to one another.

Because stablecoin contracts resemble demand deposit contracts, we can use the same model as above to calculate the distance to NQA d. In the case of stablecoins, d refers to the time and cost it takes to redeem a stablecoin, equivalent to the time it takes to get back to the issuing bank.

Data We rely primarily on two data sources: Coingecko for prices and crypto exchanges' lending rates.

We collect price, volume, and market capitalization data from Coingecko. Coingecko is a popular data provider that aggregates prices across exchanges to produce a global volume-weighted average price for each crypto security. Coingecko also calculates trading volume as the aggregate volume across all trading pairs of a cryptocurrency, and they calculate the market capitalization for currencies by multiplying the current price of the crypto asset (in

U.S. dollars) by the available supply. Coingecko also verifies the data's accuracy by dropping outliers and stale data.[21]

We collect data on 65 currencies listed as stablecoins by Coingecko between September 2014 and July 2021. For each stablecoin, we manually identify the coin's sovereign currency peg (if one exists) and convert the coin's price to U.S. dollars using spot foreign-exchange rates from Bloomberg. Stablecoins with a dollar peg dominate the stablecoin market, but pegs also include AUD, CHF, CNY, EUR, GBP, HKD, KRW, and TRY.

We clean the data as follows: we drop stablecoins where we cannot identify the peg; we drop those with fewer than 50 days of price data; we include stablecoins in our sample only after they have averaged at least $100,000 in market capitalization or volume over 30 consecutive days and we keep them in the sample from that point on, even if the average falls below the threshold; we drop three currencies that never appear to have held their peg (SAC, DSD, and USDPP); we drop data for SAI after April 24, 2020, when it transitioned to DAI; we drop three outliers (BAC before December 2020; EBASE from February 4 to 12, 2020; EBASE July 30, 2020); and, we use the previous day's price for Tether on May 29, 2019, since the observation is missing. The market capitalization and volume data for smaller stablecoins are sometimes unavailable. After these cuts, we have a sample of 44 stablecoins.

Coingecko collects and reports price data so long as they receive price data from the relevant API, and they delist assets after seven days without new information. We use historical snapshots of the stablecoin listing webpage to find delisted stablecoins. Stablecoins that are no longer stable fall into two groups: one group that continues trading despite persistently breaking its peg (e.g., Nubits/USNBT) and those that stop trading entirely (e.g., BitUSD). When coins stop trading entirely, Coingecko stops reporting data. We set the price of three delisted coins to 0 because coin holders may have suffered losses: BitUSD, NUSD, and EBASE. The Coingecko data does not suddenly stop but instead grows sparser with infrequent prices and near-zero volumes. We set the price of each coin to 0 when the sparse price and low volume pattern appears (BITUSD–8/22/2018; NUSD–4/29/2020; EBASE–10/22/2020). Binance GBP delisted after coin holders could convert to other currencies on Binance, so we do not set its price to 0 after it delists as there were no losses to our knowledge. The

[21] For example: "For coins with 1 or 2 trading pairs, any price change that is greater than 100× from the previous price will cause the new price to be classified as an outlier."

aggregate effect of these corrections is small because each coin was small relative to the stablecoin market.

Table 5 gives summary statistics for stablecoins after we clean the data. A handful of currencies dominate the total assets: the five largest stablecoins compose 95% of the total stablecoin market capitalization as of July 2021. Only four have total volume in July 2021 over $10 billion. Tether (USDT) dominates both measures, with $62 billion in market capitalization and $1.1 trillion in volume.

Unsurprisingly, most stablecoins have mean and median prices near $1.00, but some do not. No stablecoin spends more than 95% of its time at $1.00 after rounding to the nearest penny. For example, Tether's price rounds to $1.00 86.7 percent of the time, below $1.00 5.5 percent of the time, and above $1.00 about 7.7 percent of the time.

We collect lending rates on currencies provided by three large exchanges. The data are most comprehensive from one specific exchange, which we call Exchange 1. The exchange facilitates trading in many cryptocurrencies and allows direct lending of many currencies between traders for a fee.

The traders can lend or borrow at fixed terms from one day to many months. Traders can lend at either a fixed rate or, more commonly, at a spread to the exchange's calculation of the market average. Interest is charged by the second. Borrowers can repay early but must pay at least one hour of interest.

Although the exchange has not yet had losses in its lending market, there are counterparty and wallet risks.[22] The exchange imposes haircuts with an initial margin—normally set at 30% but it varies depending on the currencies. The exchange closes positions when the margin falls below 15%. The exchange says it will guarantee some losses due to counterparty risk, but its guarantee is not well-defined. Moreover, there is nontrivial wallet risk. Many exchanges have been the subject of thefts and attacks, leaving their customers with large losses.

Table 6 gives summary statistics for cryptocurrency lending. The lending rates are value-weighted rates across all transactions for a single currency on a single day, weighted by the total amount of funding. A few data features stand out: First, stablecoin lending rates are higher than lending rates for the largest cryptocurrencies: Tether's average lending rate is

[22] A *wallet* is the cryptographically-protected digital location for an agent to store cryptocurrencies on-chain, usually at a cryptocurrency exchange.

12.4% compared with Bitcoin's 8.8% or Ethereum's 6.9%. Tether's large lending rate relative to Bitcoin's and Ethereum's immediately indicates that Tether carries an inconvenience yield. Borrowers of Tether pay a high rate to entice agents to hold Tether, since there are limited other opportunities for Tether use. Second, the exchange allows lending sovereign currencies (USD, EUR, GBP, JPY), which are economically equivalent to the deposits at the exchange—in a sense, these are like non-tradable stablecoins and carry high lending rates.[23] Third, most lending on Exchange 1 occurs in only five assets: Tether, Bitcoin, Ethereum, and USD and EUR sovereigns.

The last column of Table 6 shows the average lending rates when we include data from the other two exchanges. We have interest rates from these other exchanges for USDT, DAI, BUSD, USDC, BTC, and ETH. We calculate the lending rate for a currency by first averaging across all the exchange rates available on that day for that currency and then taking an average of that time series because the time samples are not overlapping. We do not have funding amounts or funding term data for the other two exchanges. The average lending rates across all the exchanges are highly correlated.

We also use data from Bloomberg for overnight-indexed swap rates and CME cryptocurrency futures for Bitcoin. We use the CME futures data to calculate the implied-repo rate and the Bitcoin basis; we describe these calculations in section A.2.

4.2 Empirical Results

Distance to No-Questions-Asked Unlike private banknotes, stablecoins often trade at a premium to their peg. This does not imply they are more money-like when they trade at a premium: an agent who buys the stablecoin at \$1.01 suffers a 0.99% loss when the price returns to \$1.

We estimate stablecoins' distance to NQA, $\hat{d}_{it}$, by comparing its price in two locations: an exchange and the issuer. Suppose the coin trades at the exchange at price $P_t^{Ex}(d,\sigma)$ and can be redeemed or bought from its issuer at price $P_t^I(d,\sigma)$=1. If $P_t^{Ex}(d,\sigma) \neq 1$ there is an arbitrage. If $P_t^{Ex}(d,\sigma) > 1$, then an arbitrageur can buy \$1 coin from issuer and sell it at exchange for a profit. Otherwise, if $P_t^{Ex}(d,\sigma) < 1$, then the arbitrageur can buy the coin at the exchange and redeem it from the issuer at face value of \$1.

[23] One of the exchanges has a large outlier value on November 26, 2020; we drop this data point.

Let $\hat{P}(\sigma, d)$ be the price to earn a \$1 payoff from the arbitrage:

$$\hat{P}(\sigma, d) = \begin{cases} 1/\left(P_t^{Ex}(d, \sigma)\right) & \text{if } P_t^{Ex}(d, \sigma) > 1 \\ P_t^{Ex}(d, \sigma) & \text{if } P_t^{Ex}(d, \sigma) < 1 \end{cases}$$

Like banknotes, we estimate stablecoin i's distance to NQA, $\hat{d}_{it}$, using $\hat{P}(\sigma, d)$ and equation 4, although we modify a handful of the assumptions. First, we use $\hat{P}(\sigma, d)$ instead of $P(\sigma, d)$ to guarantee that the price is below \$1 because when $P(\sigma, d) > 1$ no $\hat{d}_{it}$ is small enough to solve the Black-Scholes relation. We estimate σ using the historical volatility of daily stablecoin returns over the previous quarter and require at least one month of data to estimate volatility. We estimate r_f for an arbitrary maturity from the Treasury curve each day using linear interpolation of benchmark Treasury rates . Since we do not know the value of the stablecoin issuer's assets or circulation with certainty, we assume the market value of debt and equity $V_t(d)$ is \$100. We also assume the number of coins redeemed $D_t^R(d)$ is \$1. Our results are not sensitive to this assumption so long as the ratio of the market value of equity and debt relative to the redemption amount is large.

A crucial part of our estimation is that traders can redeem their stablecoins at par from the issuer. In practice, this is not always easy. For example, Tether suspended redemptions on its website in November 2017 and reintroduced redemption in November 2018 with a minimum transaction value of \$100,000. That the arbitrage is difficult or costly—in time, transaction fees, or legwork—is precisely the friction we aim to measure with $\hat{d}_{it}$.

Figure 4 plots the value-weighted $\hat{d}_t$ and three large stablecoins' individual $\hat{d}_{it}$: Tether, Binance USD, and USD Coin. There is no obvious downward trend in $\hat{d}_t$ or $\hat{d}_{it}$, suggesting that stablecoins are not actively getting closer to becoming money over our timeframe. If anything, the average distance to NQA increased for the largest stablecoins. Tether dominates the average because it is one of the longest time series and is the largest coin. But $\hat{d}_{it}$ is highly correlated across the largest stablecoins, which is obvious from the tight behavior of the coin-specific plots.

We show the correlation of distance to NQA for stablecoins with other indicators in Table 7, many of which proxy for the stablecoin's reputation. The top panel focuses on the three largest stablecoins ranked by their one-month lagged market capitalization, and the bottom panel uses the full stablecoin sample. For the largest stablecoins—which on average compose 95% of the stablecoin market capitalization—the distance to NQA is negatively related to a time trend (-0.24), the stablecoin's age (-0.06), (logs of) volume (-0.32) and market capitalization (-0.33), the same-day return on Bitcoin (-0.02), and Bitcoin volatility (0.08). We think of the first four indicators as proxies of reputation over which the issuer has some control. We consider the Bitcoin measures as proxies for reputation in the broader cryptocurrency world, which stablecoin issuers cannot influence. The full stablecoin sample is similar, but with a key difference: the correlation between $\hat{d}_{it}$ and the time trend or the coin's age now flips signs—currencies with longer time series have a *larger* distance to NQA, suggesting that stablecoins, in aggregate, have not been successful in reducing $\hat{d}_{it}$ over time so far.

Reputation Development Stablecoins face the challenge of developing strong, independent reputations. Table 7 shows that stablecoin reputations are significantly correlated with the stablecoin's distance to NQA, and issuers spend resources to improve the reputation by disclosing their underlying assets.

Because reputation takes time to develop, stablecoin issuers' efforts to reduce d have so far followed a chaotic and nonlinear path. Perhaps the most obvious is their names; of the largest stablecoin issuers in September 2021, only four of the top twenty did not have the letters *USD* or *EUR* in their name or Coingecko tickers. For example, Tether (*USD*T), *USD* Coin (*USD*C), Binance *USD* (B*USD*), Terra*USD* (UST), True*USD* (T*USD*), and STASIS *EUR*O (*EUR*S).[24]

Efforts to reduce d go beyond names. Since stablecoins do not have bank examiners or the equivalent, many stablecoins release information about their underlying assets or reserves. But there are many approaches: some issuers do this regularly, others infrequently; some self-report, others use third-party attestations. Stablecoins also develop their reputations in qualitative ways with their terms of service. Appendix A.4 discusses these in detail.

Stablecoins' reserves, or backing collateral, are almost always held off-chain by a third party. Stablecoin issuers try to convince holders of their coins that their stablecoins are backed by reliably safe assets. Many issuers provide regular accounting reports, some more credible and transparent than others. This has led some stablecoins into legal trouble.

[24]See Appendix A.4 for details on stablecoins' names.

In April 2019, New York Attorney General (NYAG) Letitia James sued Bitfinex and Tether, both owned by Hong Kong-based iFinex, asserting that "Tether's claims that its virtual currency was fully backed by U.S. dollars at all times was a lie. These companies obscured the true risk investors faced and were operated by unlicensed and unregulated individuals and entities dealing in the darkest corners of the financial system." The NYAG closed the investigation in February 2021 with an agreement that barred New Yorkers from trading on the platforms and required Tether to report financial information about their reserves regularly.

Stablecoin issuers have also turned to regulators for an imprimatur of legitimacy. For example, the New York Department of Financial Services maintains a greenlist of currencies that allows "any entity licensed by DFS to conduct virtual currency business activity in New York may use coins on the Greenlist for their approved purpose." As of September 2021, the list includes volatile cryptocurrencies (e.g., Bitcoin, Ethereum, and Litecoin) and a handful of stablecoins (Gemini USD, Pax Standard, Binance USD, GMO JPY, and Z.com USD). Another example, Gemini USD, states on its website that "GUSD reserves are eligible for FDIC insurance up to $250,000 per user while custodied with State Street Bank and Trust." Gorton and Zhang (2021) argue that, without bank charters, stablecoins will become new versions of money-market mutual funds which operate without bank charters to this day. In November 2021, the President's Working Group on Financial Markets recommended that "legislation should require stablecoin issuers to be insured depository institutions" in order "to address risks to stablecoin users and guard against stablecoin runs." (President's Working Group on Financial Markets, 2021).

We expect a handful of salient events to have disproportionate effects on d. In Table 8, we focus on two types of events: those that affect a specific stablecoins and those that affect all stablecoins. The events that affect specific stablecoins include the New York Attorney investigation of Tether and the release of self-reported attestations and transparency reports. The events that affect all stablecoins include the announcement of new stablecoins, the day new stablecoins begin trading, and Bitcoin price crashes. The event setup helps us answer two questions: first, does d change in ways we would expect, and second, do events affect all stablecoins similarly, or are there winners and losers?

For the first event-type, we estimate a difference-in-difference regression:

$$\hat{d}_{it} = \alpha + \gamma_1 \mathbb{I}(\text{Post}) + \gamma_2 \mathbb{I}(\text{Treated}) + \gamma_3 \mathbb{I}(\text{Post}) \times \mathbb{I}(\text{Treated}) + \varepsilon_{it} \tag{7}$$

We use a window around the event of three trading dates, and we limit ourselves to a set of major stablecoins which collectively account for more than 95% of stablecoin market capitalization, on average: USDT, USDC, BUSD, DAI, USTERRA, PAX, and HUSD.

Table 8 shows the results from the difference-in-difference regression around the NYAG case: the $\mathbb{I}(\text{Post}) \times \mathbb{I}(\text{Treated})$ coefficient is not different from zero, meaning that Tether's $\hat{d}_{it}$, relative to all the other stablecoins' $\hat{d}_{it}$, did not increase. Instead, the $\mathbb{I}(\text{Post})$ is large and significantly different from zero, indicating that all stablecoins' distances to NQA increased in the three days after the announcements from the NYAG.

We also study d dynamics around publication dates of attestations and transparency reports. Many stablecoin issuers release information about their reserves, although there are many differences in the reports across firms. We focus on USDT, BUSD, USDC, and USDP since they are large issuers who have disclosed information about their reserves, and we can confidently identify the disclosure announcement date. Since USDC releases regular monthly reports, it has more events than the other currencies: USDT (3), BUSD (5), USDC (30), and USDP (3).

We report the results in column 2 for reserve transparency reports. The disclosures reduced $\hat{d}_{it}$—as we would expect if the market viewed the releases as good news—but the effect is chiefly captured by the $\mathbb{I}(\text{Post})$ coefficient, meaning that all stablecoins' $\hat{d}_{it}$'s fell, rather than only the stablecoin releasing the report. And again, the $\mathbb{I}(\text{Post}) \times \mathbb{I}(\text{Treated})$ is not different from zero, so it may be difficult for a stablecoin issuer to develop an individual reputation apart from other stablecoins.

The stablecoin-wide events include the new stablecoins' announcements (USDC, BUSD, TerraUSD, TrueUSD, PaxDollar, and HUSD), the first trading date of stablecoins in Coingecko data, and large Bitcoin price crashes. We expect these events to affect all stablecoins rather than specific ones. Therefore, we cannot test a difference-in-difference regression, and we instead estimate a simpler event study:

$$\hat{d}_{it} = \alpha + \gamma_1 \mathbb{I}(\text{Post}) + \varepsilon_{it} \tag{8}$$

We again use a window around the event of three trading dates, and we limit ourselves to major stablecoins.

In Table 8 columns 3 and 4, we test whether the announcement of new stablecoins or the opening of trading for new stablecoins affects other stablecoins' distance to NQA. There are two possible explanations: the introduction of new stablecoins could signal the broader acceptance and growing money-like characteristics of stablecoins, in which case $\gamma_1 < 0$; or it could signal increased competition among stablecoins—then $\gamma_1 > 0$. We find weak evidence for the latter; there is no significant effect on other stablecoins' $\hat{d}_{it}$s when a new coin is announced, but when a new coin begins trading, $\hat{d}_{it}$s increase a small but insignificant amount (0.08).

We test large Bitcoin crashes in column 5. We look at the five largest Bitcoin one-day price crashes since 2016 and find that $\hat{d}_{it}$ increases across all stablecoins in the days immediately after crashes. This is further evidence of a strong correlation between Bitcoin—either as a proxy for reputation in the broader cryptocurrency world or as a measure of market sentiment.

Scanning across the first row of the table, the coefficient on $\mathbb{I}(\text{Post})$, $\hat{d}_{it}$ increases the most following Bitcoin crashes (0.81) and the NYAG lawsuit (0.66) and the other events have much smaller effects. While regulatory events like the NYAG lawsuit were first-order important, Bitcoin's performance is an ever-present driver of distance to NQA.

Convenience Yield Monies farther away from no-questions-asked are less convenient to hold and use as money, so we expect that the farther stablecoins are from NQA, the lower their convenience yield—as was the case with private banknotes. We present two results related to the convenience yield: First, stablecoins' convenience yields are negative in our sample, indicating that they are not convenient to use and hold as money. Instead, they are *in*convenient. Second, we find a robust negative relationship between a stablecoin's distance to NQA and its convenience yield: the farther from NQA, the bigger the inconvenience yield. The inconvenience yield is remarkably consistent across exchanges and different combinations of stablecoins (USDT, DAI, USDC, BUSD) and cryptocurrencies (BTC, ETH, LTC).

Stablecoins do not pay interest, so we measure the stablecoin convenience yield by comparing the stablecoins' lending rate to a non-money benchmark. We calculate the convenience yield of stablecoins i on date t with

$$\text{Convenience Yield}_{it} = \text{Benchmark Yield}_t - \text{Stablecoin Yield}_{it} \tag{9}$$

We measure the convenience yield of stablecoins using cryptocurrency lending rates as the benchmark yield. Lending rates for stablecoins are high across all exchanges and all stablecoins for which we have data; it is not a feature unique to any single stablecoin. The average lending rates for USD (12.7%) and DAI (17.0%) are larger than those for Bitcoin (4.6%) and Ethereum (5.5%) over the same period.

Figure 5 plots the convenience yield for USDT, our main measure of the stablecoin convenience yield. Table 9 shows our average convenience yield estimates. When the benchmark yield is the lending rate on Bitcoin, the convenience yield is remarkably consistent across exchanges and stablecoins: it is always negative and ranges from −8.0% to −15.5%. Averaging across all exchanges, it is about −10.2% for Tether and −14.6% for DAI. We have data from only a single exchange for USDC and BUSD, but their average convenience yields are similar: −15.1% and −13.4%.[25]

Changing the benchmark comparison yield from the Bitcoin lending rate to either the CME's Bitcoin futures implied repo rate or the one-month overnight-indexed swaps rate does not change the sign of the stablecoin convenience yield. In almost all cases, using the alternative measures makes the convenience yield even more negative—likely reflecting the fact that stablecoin lending rates include a counterparty risk premium that are not present in implied repo rates or OIS rates.

One concern with our stablecoin convenience yield measures is counterparty risk. There is likely a counterparty risk premium in the lending rates. Indeed, our convenience yield estimates are lower when using the implied repo rate and OIS instead of the Bitcoin lending rate, where we expect there is a much smaller counterparty risk premium. For this reason, our preferred measure of the convenience yield in stablecoins is the spread between lending rates of Bitcoin and Tether because there is hope the counterparty risk in each leg cancels out. This measure also has the longest data history, and it is the most conservative measure because a money-like stablecoin should have a lending rate below the Bitcoin rate. The

[25]Figure A5 plots the time series of convenience yields for the four stablecoins.

measure is less negative than convenience yield when calculated using implied repo rates or OIS.

A second concern with our measure of the convenience yield is that we are mainly capturing leverage demand rather than money convenience. We argue these are two sides of the same coin. Sam Bankman-Fried, the founder of the large crypto exchange FTX, described high interest rates in crypto lending:[26]

> People in crypto want to be long \$4T. They have \$1T. The outside world is willing to lend \$0.5T, but beyond that various risk committees are like "uh idk let's get back to this one next year". So mkt cap is \$2T, and people bid up interest rates on the other \$0.5T of exposure."

People are unwilling to hold more stablecoins because of their convenience alone and instead are compelled to hold stablecoins for their unusually high lending rates. If stablecoins' distance to NQA were zero—meaning that you could use stablecoins to buy gas and groceries—more people would hold stablecoins out of convenience. Then the supply of stablecoins available to lend to traders who want leverage in crypto markets would be larger, driving lending rates down.

Relationship Between Distance to No-Questions-Asked and the Convenience Yield We expect that stablecoins that are farther from NQA will have a smaller, possibly negative, convenience yield, as shown in Proposition 1. In Table 10 we regress the convenience yield on $\hat{d}_{it}$. The first column is a panel regression for all four stablecoins with lending data. It confirms our prediction: the convenience yield is lower when $\hat{d}_{it}$ is higher. Columns 2 through 5 perform the same regression but stablecoin-by-stablecoin. The table uses Driscoll and Kraay (1998) standard errors with a maximum of 5 lags which are robust to general forms of cross-sectional and time series dependence so long as a long time series is available.

Next, we study the effect of $\hat{d}_{it}$ on the convenience yield after reasonably exogenous shocks to a stablecoin's distance to NQA. $\hat{d}_{it}$ is endogenously determined since issuers can lower it through deliberate actions. One type of shock that should consistently lower $\hat{d}_{it}$ is the launches of new Nvidia processors. Nvidia designs graphics processing units (GPUs), and

[26] See `https://twitter.com/SBF_FTX/status/1380284657820782595?s=20`

their primary business is making GPUs for playing video games. Blockchain miners also use those same GPUs to program and mine Ethereum. More powerful GPUs allow people to mine blocks faster and so improve transaction times (for Proof of Work consensus protocols, relevant for the stablecoins we study). Crypto miners compete with video game players for GPUs. Since February 2021, Nvidia has limited the mining capabilities of some new GPUs by decreasing the hashrate, and Nvidia created a separate product for crypto miners to protect their gaming customers.

Nvidia's primary business is gaming, and they design the product for gaming. Thus, we treat new launches of Nvidia GPUs as reasonably exogenous shocks to a stablecoin's distance to NQA. We study the relationship between the convenience yield on $\hat{d}_{it}$ in the three days after 21 Nvidia GPU launches for processors used in mining.[27] In Table 11 we regress the convenience yield on $\hat{d}_{it}$, restricting the sample to right after the new GPU launches. The regression introduces several controls: the Bitcoin basis, the average lending term of the stablecoin (in days), a proxy for the Treasury convenience yield (OIS−Tbill), and volume. The table also changes the dependent variables to show the result is robust to using the average convenience yield across exchanges, the convenience yield when using only Exchange 1 (where we have the richest data with the longest time series) and replacing the non-money comparison yield—the lending rate on Bitcoin in our main measure—with the implied repo rate or overnight-indexed swap rates.

Combined, we find that the stablecoin convenience yield is consistently negative across several stablecoins and exchanges. Equivalently, we find there is a stablecoin inconvenience yield. The stablecoin convenience yield is strongly negatively related to the coin's distance to NQA. As stablecoin issuers make their coins more money-like, we expect they would develop a convenience yield like private banknotes did almost 200 years before.

5 Comovement within Banknotes and Stablecoins

During bank runs, bank depositors scramble to withdraw deposits. Since prices are fixed at \$1, declining quantities are the only margin of adjustment. We study the correlation

[27] This result is robust to using a different horizon after the launches. We list the release dates for the processors in Table A4. We include GPUs with release dates corresponding to when we have data on $\hat{d}_{it}$ and the average convenience yield across exchanges.

of changes in quantity for stablecoins and private banknotes to show that stablecoins are runnable like private banknotes.

We show two results: first, the largest issuers' volume growth is tightly correlated. We calculate the average correlation of private banknotes by aggregating circulation to the state level and then comparing circulation growth rates across each of the 30 states. For stablecoins, we compare daily changes in volume for each stablecoin.

Figure 6 shows the average pairwise correlation. We sort states' circulation in decreasing order and use the states that make up 95% of the total circulation as the states with the biggest private banknotes. The changes in circulation are more correlated for this set of the largest states' banknotes circulation. The full set of stablecoins have an average correlation of 14%, and the largest three stablecoins—Tether, USDC, and Binance USD—have a correlation of 47%. Combined, the biggest issuers of a private money face declines in volume simultaneously.

The correlation between stablecoins' volume changes is not surprising. Consistent with the event studies in Table 8, the correlation results suggest that it is difficult for stablecoins to develop an individual reputations and market participants seem to treat stablecoins as a group. The lack of differentiation in reputation across stablecoins serves as a challenge for an issuer's efforts to reduce the distance to NQA for a specific stablecoin.

Second, we show that the correlations increase during crises, indicating the runnable quality of private banknotes and stablecoins. We calculate rolling correlations over a three-year period for private banknotes and every month for stablecoins. Figure 6 plots the average correlation in non-crisis periods compared to crisis periods. For stablecoins, an unpaired t-test shows that the correlation is significantly higher in crisis periods which we define as months with the worst 5% of Bitcoin returns. The correlation is slightly higher in crisis for private banknotes but not statistically different from non-crisis times.

The correlations show that the largest stablecoins' volumes are highly correlated, and volume changes are more correlated in times of stress. Although the data frequency and periods are different, the results suggest that stablecoins are more runnable than historical private banknotes.

6 Conclusion

In the nineteenth century, private debt often circulated as money—Schuler (1992) finds about 60 instances across many countries. But these monies were supplanted by government-produced money. Stablecoins are the most recent example of privately-produced debt trying to become money. We studied U.S. pre-Civil War private banknotes to understand how stablecoins might evolve.

We summarized the state of a private money by calculating its distance from NQA, d, which we showed drives the money's convenience yield. Technological change and reputation development reduce d. Pre-Civil War U.S. banknotes eventually had a positive convenience yield, although they always traded at a discount when used far from the issuing bank. Currently, stablecoins have an inconvenience yield. But, like banknotes, technological change decreases the inconvenience yield. Stablecoins have not developed individual reputations, nor are they accepted as money, no-questions-asked. As a result, stablecoins do not yet earn a positive convenience yield.

It is an open question whether private forms of money can reduce their distance to NQA to zero. We are unaware of any examples of widely circulating private money that is NQA, $d = 0$, without government backing, either implicit or explicit. A credible government can create NQA debt, and that debt can take many forms: physical currency, central bank reserves, or insured bank deposits. Like private banknotes before them, stablecoins may need a government guarantee to become NQA. Left to their own devices, stablecoins may still have success decreasing their distance to NQA. Historically, though, money that is NQA is a public good that only the government can supply.

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7 Figures

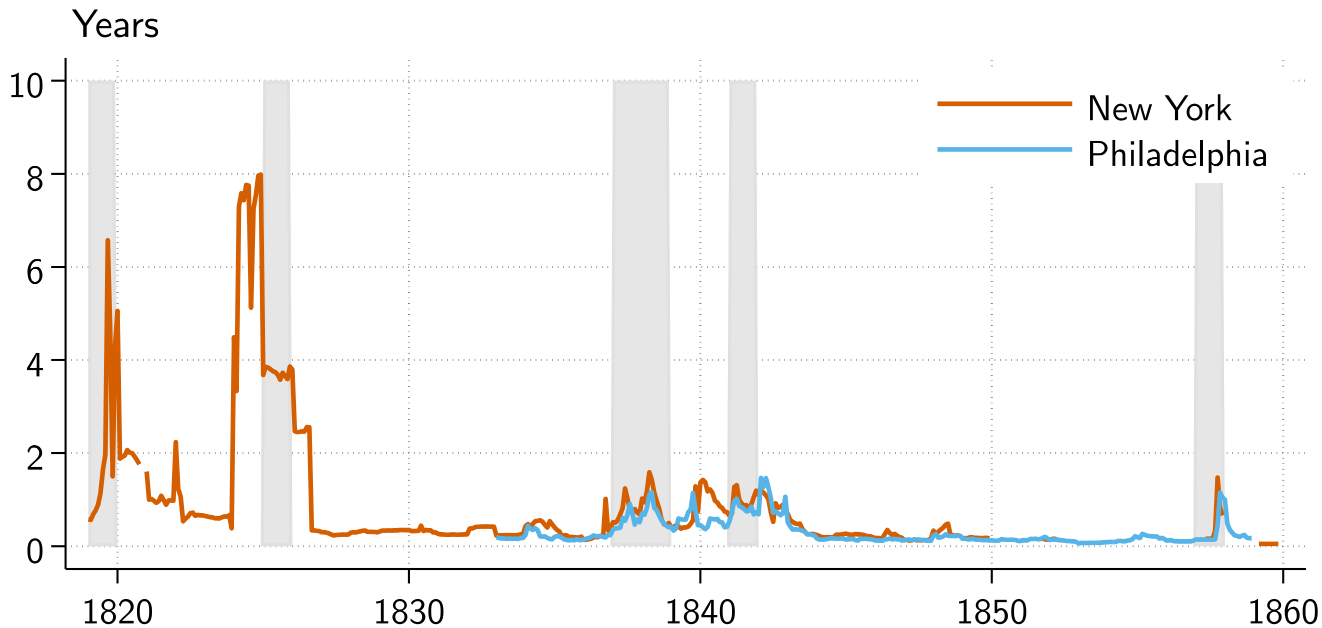

Figure 1: Banknotes Distance to No-Questions-Asked $\hat{d}_t$ Figure plots the average distance to NQA $\hat{d}_t$ estimated following the method described in section 3.2. The two lines reflect estimates based on where the bank quote is provided: either New York or Philadelphia. Average $\hat{d}_t$ is value-weighted using the bank's share of lagged circulation.

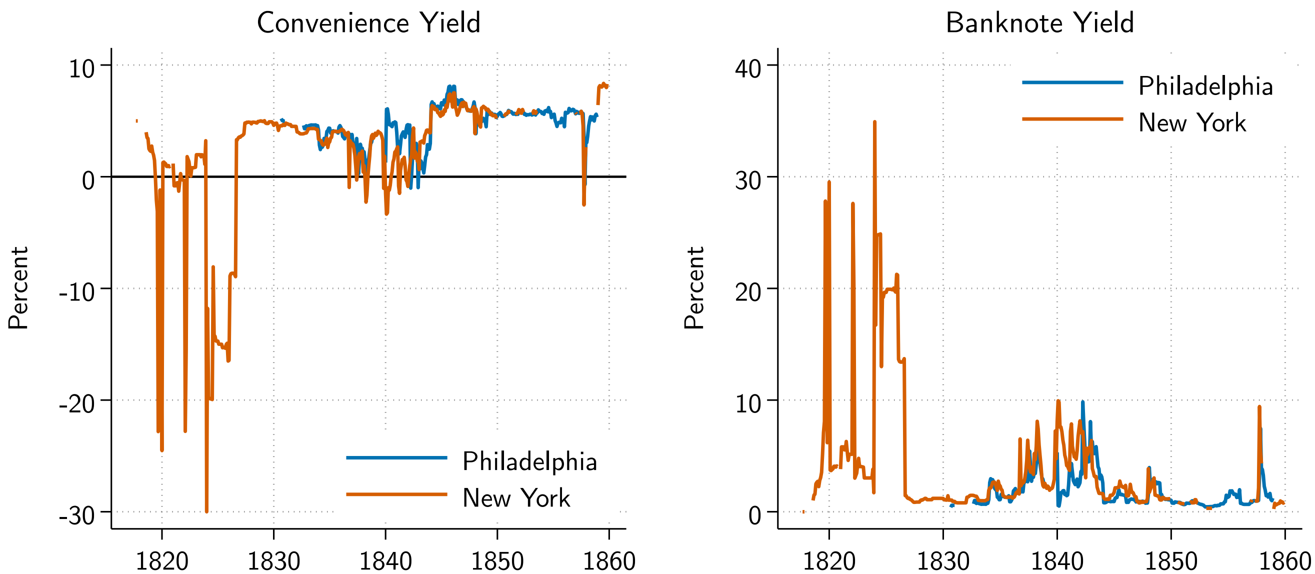

Figure 2: Pre-Civil War Banknote Convenience Yields The left panel plots the average convenience yield across all banknotes quoted in either New York or in Philadelphia, described in equation 6. Convenience yield is $y^{Aaa} - y^{Banknote}$, where y^{Aaa} is the Moody's Aaa corporate bond index from Global Financial Data and $y^{Banknote}$ is the average banknote yield across all banks with quotes in that month and weighted by banks' previous year's circulation share. The right panel plots $y^{Banknote}$, the second component in the convenience yield plotted on the left.

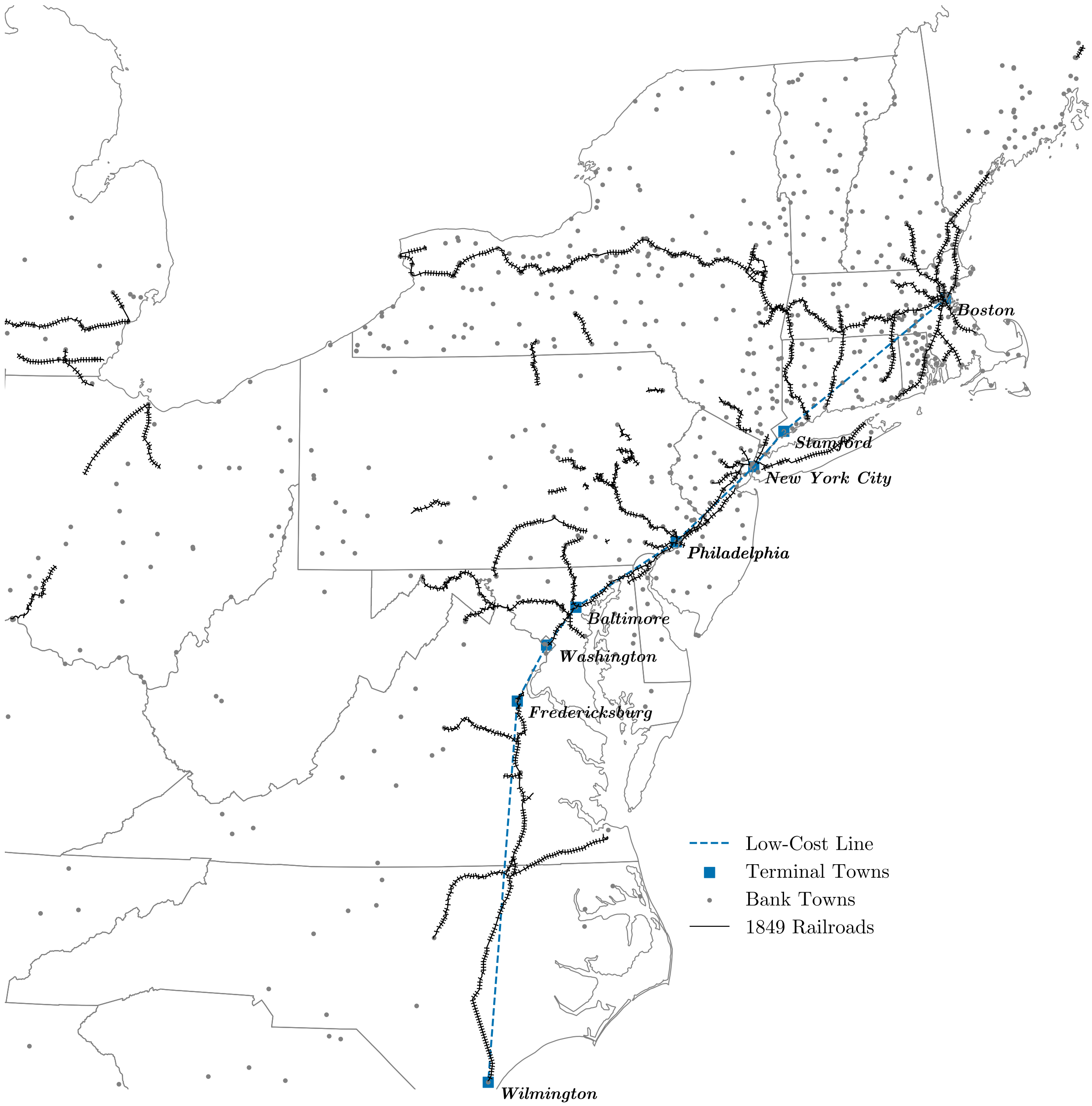

Figure 3: 1849 Railroad Network Figure plots the railroad network in 1849, the low-cost line, and towns that have a bank at any point in our data. Bank towns are from Weber (2021) and railroad network is from Atack (2016).

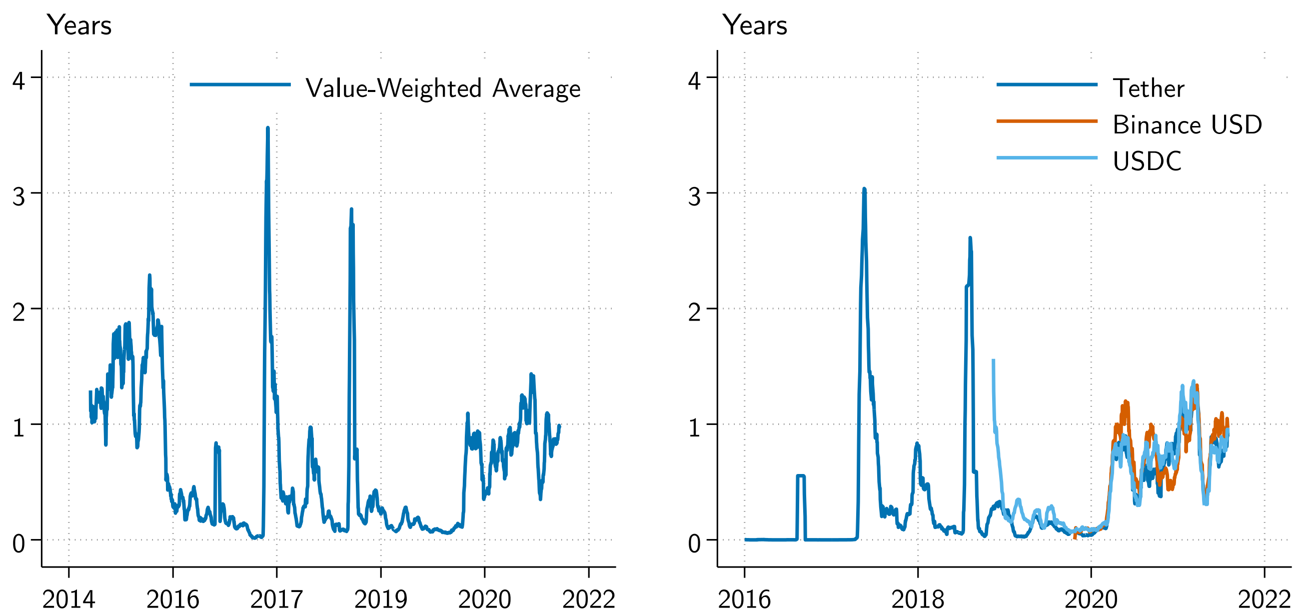

Figure 4: Stablecoins Distance to No-Questions-Asked $\hat{\boldsymbol{d}}_{\boldsymbol{t}}$ Left panel plots the value-weighted average distance to NQA $\hat{d}_t$ estimated following the method described in section 4.2 where value-weights use the previous month's market capitalization. The right panel plots $\hat{d}_t$ for three large stablecoins: Tether (USDT), Binance USD (BUSD), and USD Coin (USDC). Each timeseries plots the one-month moving average of $\hat{d}$.

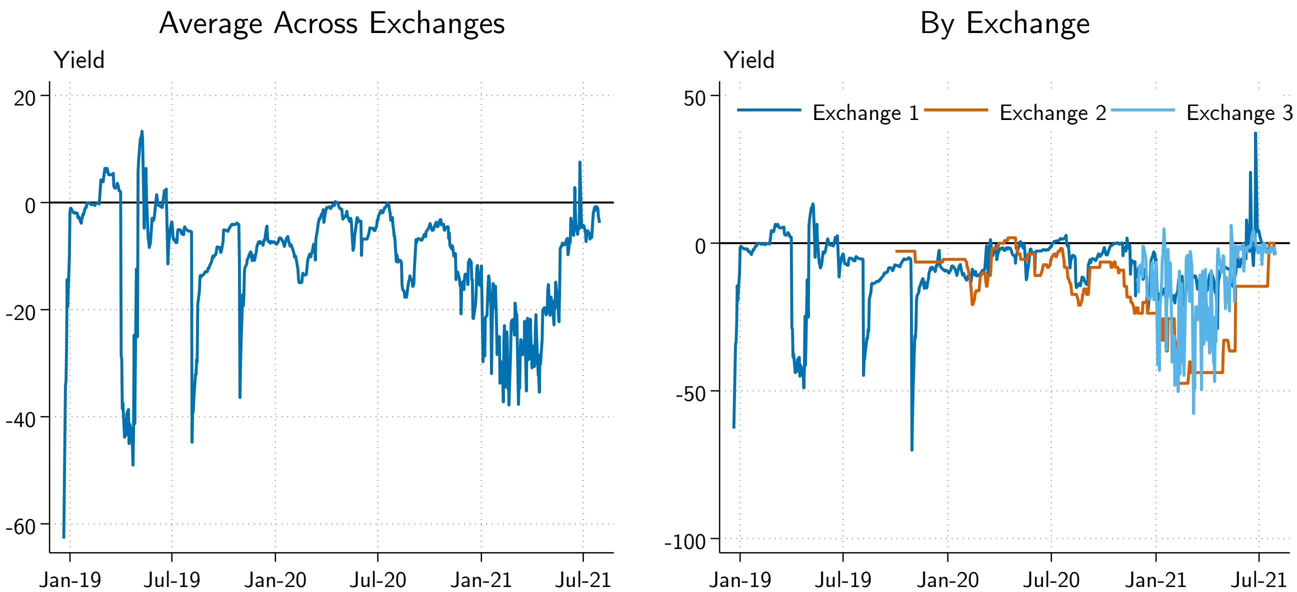

Figure 5: Stablecoin Convenience Yield The left panel plots the average convenience yield across all exchanges, where the convenience yield is calculated using lending rates for Tether and Bitcoin. Convenience yield is $y^{BTC} - y^{USDT}$. The right panel plots the convenience yield across the three exchanges.

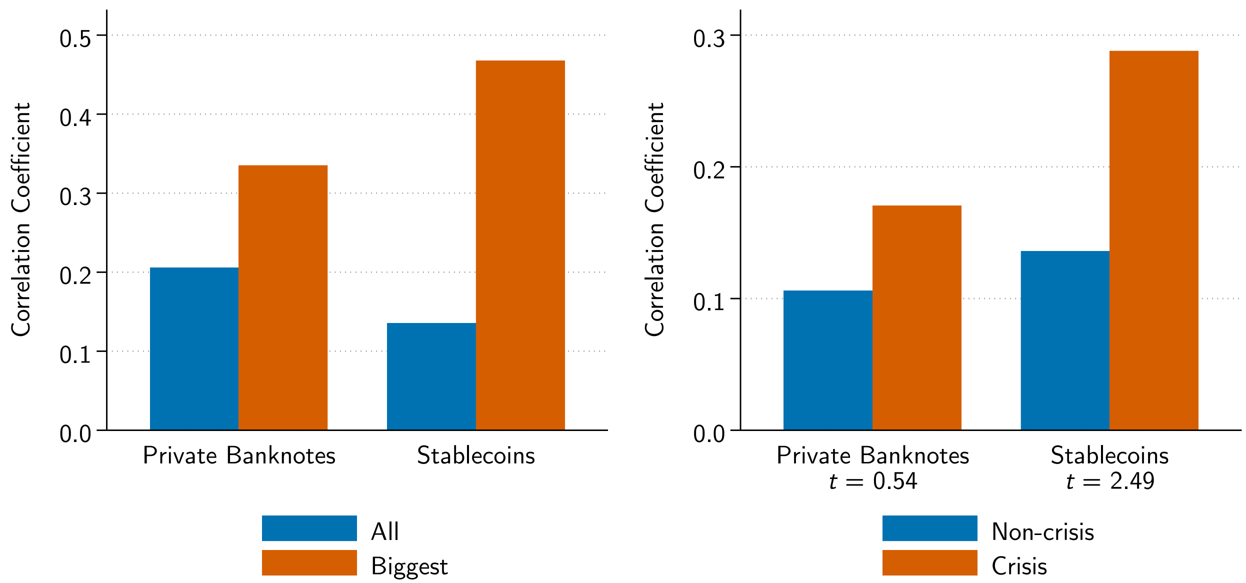

Figure 6: Average Correlation of Changes in Volume Figure plots pairwise correlation of changes in log volume. The left panel plots the average pairwise correlation. The biggest private banknotes include states that make up 95% of the total circulation, and the biggest stablecoins are Tether, USDC, and BUSD. The right panel plots the average rolling correlation in crisis and non-crisis periods. Crisis periods for private banknotes are from Trebesch et al. (2021), and crisis months for stablecoins are the worst 5% of Bitcoin returns. t-statistics correspond to unpaired t-tests of the correlations in crisis and non-crisis periods within each form of private money.

8 Tables

	Correlation of Distance to No-Questions-Asked $\hat{d}_{it}$ with:					
	d_{it} (Days)	Travel Cost (\$)	Time Trend	Age	$\mathbb{I}$(Crisis)	$\mathbb{I}$(Free Banking)
Philadelphia-Based Quotes						
ρ	0.21^{***}	0.18^{***}	-0.05^{***}	-0.11^{***}	0.06^{***}	-0.01^{*}
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)
N	373	373	117,814	117,814	117,814	117,814
New York-Based Quotes						
ρ			-0.14^{***}	-0.05^{***}	0.04^{***}	-0.06^{***}
p-value			(0.00)	(0.00)	(0.00)	(0.00)
N			48,451	48,451	48,451	48,451

Table 1: Banknote Distance to NQA Correlations. Table presents the correlation of banknote distance to no-questions-asked $\hat{d}_{it}$ with a selection of variables, including the travel time and cost (compiled by Gorton 1989), a time trend, the bank's age, and indicator variables for crises (from Trebesch et al. 2021) and whether the bank is in a Free Banking state using Gorton (1999). We limit the sample in the first two columns to banks in cities and years with travel data (from Philadelphia) listed in Gorton (1989) and we collapse to a bank-by-year level using the median banknote quote. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

New York Quotes	Mean	Median	Std. Dev.	Min	Max
Convenience Yield (Corporate Bond Benchmark)					
Full Sample	2.07	3.94	6.00	−30.00	8.36
Post-1835	4.18	5.46	2.55	−3.35	8.36
Convenience Yield (Municipal Bond Benchmark)					
Full Sample	1.00	3.03	5.53	−30.00	5.94
Post-1835	2.41	3.12	2.03	−4.38	4.67
Banknote Yields					
Full Sample	3.99	1.74	5.54	0.00	34.93
Post-1835	2.67	1.74	2.21	0.25	9.94
Philadelphia Quotes	Mean	Median	Std. Dev.	Min	Max
Convenience Yield (Corporate Bond Benchmark)					
Full Sample	4.73	5.13	1.66	−1.02	8.11
Post-1835	4.82	5.54	1.76	−1.02	8.11
Convenience Yield (Municipal Bond Benchmark)					
Full Sample	3.14	3.59	1.37	−4.06	5.08
Post-1835	3.15	3.74	1.46	−4.06	5.08
Banknote Yields					
Full Sample	1.80	1.22	1.49	0.40	9.84
Post-1835	1.89	1.27	1.57	0.43	9.84
Bond Indices	Mean	Median	Std. Dev.	Min	Max
Corporate Bond Index Yield					
Full Sample	6.08	6.00	1.04	4.60	9.62
Post-1835	6.77	6.59	0.87	5.47	9.62
Municipal Bond Index Yield					
Full Sample	5.01	4.95	0.51	4.13	6.25
Post-1835	5.03	4.98	0.28	4.48	5.99

Table 2: Pre-Civil War Convenience Yields. Table presents summary statistics of the value-weighted aggregate convenience yield, banknote yield, corporate bond index yield, and municipal bond index yield in percent. The convenience yield is measured as: $\text{Convenience Yield}_{it} = \text{Benchmark Yield}_{t-1} - \text{Banknote Quote}_{it}/(100 - \text{Banknote Quote}_{it})$, where the benchmark yield is either the corporate bond index or the municipal bond index. Value-weights are calculated using lagged circulation share of banks quotes in the same city (e.g., of all banks with quotes in Philadelphia) derived from bank balance sheet data from Weber (2018b). Corporate bond and municipal bond indices are from Global Financial Data. Banknote yields are the calculated using the right-most expression in the convenience yield equation. The first 6 rows calculate yields using quotes based mainly in New York and compiled by Weber (2021); the second group of rows perform the same calculations using banknote quotes based in Philadelphia with data from Weber (2021). The full sample runs from 1817 to 1858 for New York quotes and the bond indices; the full sample for Philadelphia quotes runs from 1830 to 1858.

	Corporate Bond Convenience Yield				Municipal Bonds Convenience Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
d_{it} (Travel Time, Days)	-0.26^{***}	-0.18^{***}	-0.23^{***}	-0.18^{**}	-0.21^{***}	-0.19^{***}	-0.24^{***}	-0.20^{**}
	(-4.67)	(-4.72)	(-5.53)	(-2.18)	(-4.93)	(-5.24)	(-6.00)	(-2.38)
ln(Assets)			0.37	0.09			0.37	0.07
			(1.19)	(0.29)			(1.19)	(0.23)
N	373	373	373	373	373	373	373	373
R^2	0.06	0.11	0.14	0.39	0.04	0.04	0.07	0.10
Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bank FE	No	No	No	Yes	No	No	No	Yes

Table 3: Distance to No-Questions-Asked *d* and Pre-Civil War Convenience Yield. Table presents the results from regressing bank i's convenience yield at time t on the travel time compiled by Gorton (1989). We limit the sample in the following way: first, we limit the sample to quotes provided in Philadelphia because the travel data is relative to Philadelphia; second, we match the travel data from 1862 to 1858 quotes since we have no quotes data for 1862; third, we use the median quote in each year we have travel data (1836, 1849, 1862) for each bank. Columns (1) through (3) use the convenience yield calculated with the corporate bond index as the benchmark yield, and columns (4) through (6) calculate the convenience yield using the municipal bond index. t-statistics are reported in parentheses using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Second Stage

Instrument	Convenience Yield: Distance to Low-Cost Line (1)	(2)	(3)	Within 30 Miles of Low-Cost Line (4)	(5)	(6)
Time to Philadelphia	−0.198**			−0.473***		
	(−2.236)			(−3.040)		
Cost to Philadelphia		−0.029**			−0.064***	
		(−2.254)			(−3.055)	
Distance to Philly Network			−0.002**			−0.005***
			(−2.266)			(−3.064)
N	337	337	337	337	337	337
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: First Stage

	(1) Time	(2) Cost	(3) Dist. to Philly Network	(4) Time	(5) Cost	(6) Dist. to Philly Network
Dist. to Low-Cost Line	0.012***	0.080***	0.938***			
	(27.623)	(36.955)	(22.909)			
Within 30 Miles of Low-Cost Line				−0.956***	−7.048***	−94.276***
				(−9.737)	(−10.513)	(−10.556)
F-stat	763	1,366	525	95	111	111

Panel C: OLS

	Convenience Yield (1)	(2)	(3)	(4)	(5)	(6)
Time to Philadelphia	−0.158*			−0.158*		
	(−1.869)			(−1.869)		
Cost to Philadelphia		−0.024*			−0.024*	
		(−1.953)			(−1.953)	
Distance to Philly Network			−0.002**			−0.002**
			(−2.096)			(−2.096)
N	337	337	337	337	337	337
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Instrumental Variables Regression of Distance to No-Questions-Asked *d* and Pre-Civil War Convenience Yield. We use two instruments—distance to the low-cost line and an indicator for whether the bank is within 30 miles of the low-cost line—to predict three measures of the d_{it} variable: the time to travel to Philadelphia, the cost to travel to Philadelphia, and the minimum distance to the Philadelphia railroad network. Panel A shows the second stage regression of the instrumented variables on the convenience yield. Panel B shows the first stage regression of the instruments on the d_{it} variables. Panel C shows the OLS regression of the d_{it} variables on the convenience yield. t-statistics are reported in parentheses using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

		July 2021 Characteristics			Price					Price Relative to $1 (% of N)		
	Ticker	N	Market Cap. ($ mln)	Volume ($ mln)	Mean	Median	St. Dev.	Min	Max	Below $1	At $1	Above $1
1	USDT	1,661	62,390	1,095,432	1.00	1.00	0.02	0.57	1.32	0.06	0.87	0.08
2	USDC	729	26,450	47,553	1.00	1.00	0.01	0.98	1.04	0.03	0.83	0.14
3	BUSD	485	11,131	77,409	1.00	1.00	0.00	0.98	1.01	0.03	0.94	0.03
4	DAI	444	5,260	11,838	1.00	1.00	0.01	0.93	1.06	0.08	0.53	0.39
5	USTERRA	177	1,981	983	1.00	1.00	0.01	0.96	1.04	0.10	0.61	0.29
6	TUSD	876	1,402	1,500	1.00	1.00	0.01	0.94	1.07	0.06	0.79	0.15
7	PAX	743	906	1,308	1.00	1.00	0.01	0.98	1.04	0.06	0.82	0.13
8	LUSD	85	629	127	1.01	1.01	0.01	0.97	1.07	0.06	0.15	0.79
9	HUSD	486	561	1,551	1.00	1.00	0.00	0.97	1.05	0.04	0.90	0.06
10	USDN	390	407	596	1.00	1.00	0.01	0.95	1.02	0.27	0.65	0.09
11	FEI	85	354	567	0.96	1.00	0.07	0.71	1.01	0.49	0.38	0.13
12	GUSD	732	286	224	1.00	1.00	0.01	0.89	1.11	0.23	0.57	0.20
13	FRAX	160	230	226	1.00	1.00	0.01	0.98	1.03	0.17	0.50	0.33
14	ALUSD	50	230	94	1.00	1.00	0.01	0.97	1.04	0.04	0.60	0.36
15	SUSD	777	229	1,592	0.99	1.00	0.03	0.44	1.09	0.48	0.23	0.30
16	SEUR	143	148	31	1.01	1.01	0.01	0.98	1.07	0.08	0.22	0.69
17	USDP	122	111	65	0.99	1.00	0.04	0.81	1.19	0.34	0.19	0.47
18	EURS	783	106	13	1.00	1.00	0.02	0.92	1.09	0.46	0.30	0.24
19	VAI	127	80	29	0.92	0.91	0.04	0.85	1.04	0.95	0.02	0.03
20	USDX	187	69	6	0.86	0.84	0.10	0.68	1.02	0.82	0.15	0.03
21	TRYB	359	57	51	0.99	0.99	0.01	0.95	1.04	0.58	0.30	0.11
22	CUSD	182	52	27	1.00	1.00	0.00	0.98	1.02	0.07	0.79	0.14
23	KRT	531	40	2	1.00	1.00	0.01	0.88	1.06	0.48	0.42	0.10
24	MUSD	273	36	6	1.00	1.00	0.01	0.96	1.08	0.16	0.59	0.25
25	ESD	230	34	11	0.64	0.20	1.17	0.04	10.47	0.76	0.04	0.20
26	USDK	546	33	2,645	1.00	1.00	0.01	0.97	1.03	0.21	0.70	0.09
27	DUSD	199	30	14	1.00	1.00	0.03	0.84	1.19	0.28	0.33	0.39
28	OUSD	209	19	1	0.86	1.00	0.31	0.15	1.04	0.49	0.37	0.15
29	RSV	342	8	3	1.00	1.00	0.03	0.79	1.13	0.21	0.52	0.27
30	BITCNY	1,610	6	18	1.00	1.00	0.19	0.28	6.47	0.40	0.20	0.40
31	EOSDT	566	5	0	1.00	1.00	0.01	0.87	1.08	0.39	0.43	0.17
32	BAC	160	4	3	0.37	0.30	0.29	0.07	1.21	0.83	0.01	0.16
33	PAR	94	3	2	1.00	1.00	0.03	0.87	1.09	0.38	0.16	0.46
34	USNBT	1,710	0	0	0.58	0.71	0.42	0.00	1.26	0.67	0.21	0.12
35	USDS	640	0	0	1.02	1.00	0.25	0.67	5.42	0.28	0.41	0.31
36	QC	593	0	6,399	1.00	1.00	0.01	0.95	1.04	0.40	0.37	0.23
37	EBASE	481	0	0	0.54	0.85	0.48	0.00	1.23	0.80	0.11	0.09
38	XDAI	109	0	16	1.00	1.00	0.00	0.99	1.01	0.03	0.79	0.18
39	IRON	84	0	1	0.93	0.99	0.10	0.74	1.02	0.55	0.33	0.12
40	WUST	57	0	40	1.00	1.00	0.01	0.94	1.03	0.18	0.35	0.47
41	BITUSD	1,763		0	0.58	0.98	0.51	0.00	1.42	0.55	0.09	0.36
42	SAI	608		0	1.00	1.00	0.01	0.96	1.09	0.24	0.40	0.36
43	NUSD	571		0	0.42	0.00	0.49	0.00	1.03	0.64	0.33	0.03
44	BGBP	336		0	1.00	1.00	0.01	0.94	1.05	0.26	0.22	0.52

Table 5: Stablecoin Summary Statistics. Table presents summary statistics of our sample of stablecoins from Coingecko. N is the number of days we have price data. Market capitalization is July 2021 market cap, in millions of dollars. Volume is total volume in July 2021, in millions of dollars. "Price relative to $1" columns define above and below $1 after rounding the price to the nearest penny.

	Ticker	Exchange 1								All Exchanges
		N (Days)	Mean (Percent)	Median (Percent)	St. Dev. (Percent)	Min (Percent)	Max (Percent)	Avg. Funding ($ mln)	Avg. Term (Days)	Mean (Percent)
Stablecoins	USDT	681	12.4	11.0	9.9	0.1	70.7	39.0	20.4	16.0
	DAI	267	17.0	4.3	38.8	0.0	199.8	0.0	40.4	18.7
	BUSD	469	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	23.4
	USDC	479	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	25.1
Sovereign	USD	2,186	26.7	18.8	27.1	1.9	274.4	2111.7	20.2	26.7
	EUR	975	14.6	9.1	16.0	0.3	156.1	21.5	13.3	14.6
	GBP	863	14.8	6.5	26.3	0.0	279.0	1.3	15.8	14.8
	JPY	865	17.1	12.0	19.5	0.3	213.2	0.3	14.7	17.1
Other	BTC	2,193	8.8	5.3	10.8	0.0	109.9	1179.5	18.3	9.2
	ETH	1,402	6.9	4.0	9.0	0.3	106.8	264.1	8.9	7.5
	BSV	674	8.1	5.6	8.8	0.0	45.8	12.1	14.1	8.1
	ETC	1,294	12.0	3.4	21.9	0.0	210.2	9.0	9.9	12.0
	EOS	1,058	7.2	0.7	17.6	0.0	140.4	7.0	12.3	7.2
	LTC	2,101	6.7	3.3	11.3	0.0	164.1	6.4	15.9	6.7
	XMR	1,138	4.9	2.5	8.9	0.0	92.9	5.0	9.3	4.9
	XRP	1,040	4.2	0.9	13.3	0.0	154.1	3.9	8.7	4.2
	NEO	1,003	13.2	5.9	20.7	0.0	160.4	2.1	9.9	13.2
	MIOTA	1,058	1.1	0.1	3.3	0.0	52.2	2.0	9.8	1.1
	BTG	931	18.8	9.6	25.5	0.0	232.1	1.5	14.7	18.8
	ADA	230	23.5	2.9	45.8	0.0	173.9	1.5	20.1	23.5
	DASH	1,138	8.8	4.0	14.6	0.0	176.1	1.0	10.0	8.8
	UNI	211	18.1	13.5	19.7	0.0	105.6	0.8	20.3	18.1
	OMG	1,034	6.3	1.7	12.7	0.0	130.3	0.7	10.2	6.3
	DOT	237	9.3	0.1	30.7	0.0	178.0	0.6	17.6	9.3
	BCH	112	2.1	0.0	10.4	0.0	74.1	0.4	20.9	2.1
	LINK	237	4.9	0.3	17.2	0.0	157.7	0.3	14.4	4.9
	YFI	181	33.2	28.9	37.3	2.8	265.8	0.3	29.2	33.2
	DOGE	57	14.1	1.9	25.9	0.4	124.7	0.3	13.3	14.1
	ZEC	1,197	5.4	1.6	11.3	0.0	134.0	0.2	7.8	5.4
	FIL	173	62.2	32.9	69.0	0.0	230.5	0.2	23.5	62.2
	XLM	506	6.0	0.5	20.1	0.0	301.0	0.1	13.6	6.0
	XTZ	506	7.1	4.2	11.7	0.0	123.1	0.1	14.7	7.1
	SOL	38	9.1	3.1	10.4	0.0	34.4	0.1	17.3	9.1
	SUSHI	131	22.1	13.2	24.1	0.0	132.0	0.1	16.9	22.1
	TRX	231	14.5	5.2	20.1	0.0	106.6	0.1	19.6	14.5
	ZRX	721	7.2	3.7	14.1	0.0	187.6	0.1	8.6	7.2
	PNT	975	10.1	1.3	26.2	0.0	243.8	0.1	17.2	10.1
	LEO	561	1.0	0.0	12.1	0.0	177.9	0.1	25.3	1.0
	ATOM	367	8.3	0.8	16.0	0.0	111.0	0.0	27.2	8.3
	XAUT	385	5.3	0.0	25.5	0.0	231.4	0.0	23.9	5.3
	ALGO	362	10.1	4.1	19.4	0.0	144.1	0.0	23.5	10.1
	FTT	359	25.3	0.5	43.5	0.0	182.5	0.0	10.3	25.3
	SAN	1,003	11.3	0.1	36.2	0.0	384.0	0.0	12.4	11.3
	ETP	979	12.7	0.8	32.5	0.0	228.7	0.0	12.0	12.7

Table 6: Cryptocurrency Lending Summary Statistics. Table gives summary statistics for currency lending rates. Lending rates are annualized. The first eight columns plot the statistics from our primary source of data, Exchange 1. The last column gives the average funding rate across all three exchanges; in many cases we only have data from exchange 1. Average funding is the average funding used in dollar terms. "Avg. Term" is the average term of lending in days. Summary statistics calculated over the time series available for that currency rather than over a concurrent sample. *n.a.* denotes not available.

Correlation of Distance to No-Questions-Asked $\hat{d}_{it}$ with:						
	Time Trend	Age	Volume	Market Capitalization	Bitcoin Return	Bitcoin Volatility
Three Largest Stablecoins						
ρ	-0.24^{***}	-0.06^{***}	-0.32^{***}	-0.33^{***}	-0.02^{*}	0.08^{***}
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.00)
N	4,914	4,914	4,908	4,914	4,911	4,911
Full Stablecoin Sample						
ρ	0.10^{***}	0.05^{***}	-0.20^{***}	-0.17^{***}	-0.02^{**}	0.06^{***}
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)
N	19,138	19,138	18,895	16,576	19,135	19,099

Table 7: Stablecoin Distance to No-Questions-Asked Correlations. Table presents the correlation of stablecoin distance to no-questions-asked $\hat{d}_{it}$ with a selection of variables, including a time trend, the stablecoin's age, logs of the stablecoin's volume and market capitalization, Bitcoin's return, and Bitcoin's volatility (constructed using daily returns over the week). Three largest stablecoins limits the sample to stablecoins ranked in the top three by market capitalization in the previous month. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	NYAG Lawsuit	Attestations	New Stablecoin Announced	New Stablecoin Starts Trading	Bitcoin Crashes
$\mathbb{I}$(Post)	0.66***	−0.10*	−0.07	0.08	0.81***
	(4.54)	(−1.69)	(−0.76)	(1.44)	(3.67)
$\mathbb{I}$(Treat)	−0.04	−0.05			
	(−0.13)	(−0.74)			
$\mathbb{I}$(Post) $\times$ $\mathbb{I}$(Treat)	−0.11	0.08			
	(−0.37)	(0.99)			
N	70	1,450	91	1,350	70
R^2	0.61	0.41	0.89	0.37	0.70
Events	2	41	6	42	5
Coin FE	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Event Study of Stablecoin Distance to No-Questions-Asked *d*. Table presents the regression of stablecoin i's distance to no-questions-asked $\hat{d}_{it}$ on dummies for treatment and post around the events: $\hat{d}_{it} = \alpha + \gamma_1 \mathbb{I}(\text{Post}) + \gamma_2 \mathbb{I}(\text{Treated}) + \gamma_3 \mathbb{I}(\text{Post}) \times \mathbb{I}(\text{Treated}) + \varepsilon_{it}$. Each column corresponds to a different event study: the New York Attorney General opening and closing its investigation into Tether (4/25/2019 and 2/23/2021) where Treated = 1 for Tether; attestations are releases of attestations and transparency reports, where Treated = 1 for the stablecoin issuer releasing the report, which include USDT, BUSD, USDC, and USDP. New stablecoin announced refers to the announcement date of USDC, BUSD, TerraUSD, TrueUSD, PaxDollar, and HUSD. First trade date is the first date of price is available for the USD-pegged stablecoins on Coingecko. Bitcoin crashes events are the 5 largest single-day Bitcoin declines since 2016. The window around each event is 3 business days before and after the event date. We limit the sample to major stablecoins, which we define as USDT, USDC, BUSD, DAI, USTERRA, PAX, and HUSD. t-statistics are reported in parentheses using robust standard errors, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

		Bitcoin Lending Rate		Implied Repo Rate		Overnight-Indexed Swap	
Stablecoin	Exchange	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
USDT	Average	−10.2	10.8	−15.9	10.7	−15.0	11.0
	Exchange 1	−8.0	10.3	−12.3	9.9	−11.4	9.9
	Exchange 2	−15.5	13.9	−25.2	15.6	−24.9	15.9
	Exchange 3	−13.4	14.1	−15.4	13.7	−15.4	13.9
DAI	Average	−14.6	37.2	−18.6	37.9	−18.6	37.8
	Exchange 1	−12.4	38.3	−16.8	38.8	−16.9	38.8
	Exchange 3	−12.8	16.3	−14.5	15.8	−14.4	15.8
USDC	Exchange 2	−15.1	14.1	−24.9	16.1	−24.6	16.5
BUSD	Exchange 2	−13.4	13.2	−23.2	15.3	−23.0	15.6

Table 9: Stablecoin Convenience Yields Summary Statistics. Table reports summary statistics for stablecoin convenience yields in annual percent. Convenience yields are calculated using stablecoin lending rates relative to the Bitcoin lending rate, implied repo rate, and OIS rate. Average exchange refers to the average lending rate across exchanges, which is calculated for stablecoins with data available from multiple exchanges.

	(1) All	(2) USDT	(3) USDC	(4) BUSD	(5) DAI
$\hat{d}_{it}$	-8.08^{***}	-2.47^{**}	-6.69^{***}	-3.70^{**}	-10.95^{***}
	(-3.59)	(-2.14)	(-3.63)	(-2.29)	(-3.18)
N	1,889	680	479	463	267
R^2	0.15	0.02	0.08	0.03	0.27
Coin FE	Yes				

Table 10: Distance to No-Questions-Asked *d* and Stablecoin Convenience Yield. Table gives estimates from regressing a stablecoin's convenience yield on its estimated distance to NQA, $\hat{d}_{it}$. Observations are stablecoin by day. The first column presents a pooled regression including USDT, USDC, BUSD, and DAI, where the convenience yield is the average convenience yield calculated across the three exchanges. Column 1 R^2 is within-R^2. t-statistics using Driscoll and Kraay (1998) standard errors with a maximum of 5 lags are reported in parentheses, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Avg. Across Exchanges		Exchange 1		Implied Repo Rate		OIS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{d}_{it}$	-11.84^{***}	-11.06^{**}	-11.68^{***}	-10.71^{**}	-12.18^{***}	-11.04^{**}	-12.10^{***}	-11.04^{**}
	(−3.36)	(−2.59)	(−2.88)	(−2.43)	(−2.98)	(−2.50)	(−2.96)	(−2.50)
Bitcoin Basis		−0.20		−0.22		−0.18		−0.20
		(−1.59)		(−1.46)		(−1.16)		(−1.30)
Bitcoin Return		0.06		0.35		0.22		0.23
		(0.13)		(0.70)		(0.44)		(0.45)
Average Term		-0.54^{*}		-0.56^{*}		-0.57^{*}		-0.56^{*}
		(−1.73)		(−1.69)		(−1.70)		(−1.69)
OIS−Tbill		−94.04		−137.41		−138.41		−140.11
		(−1.53)		(−1.62)		(−1.65)		(−1.66)
ln(Volume)		−0.50		−1.45		−2.29		−2.32
		(−0.28)		(−0.72)		(−1.14)		(−1.15)
N	204	108	108	108	108	108	108	108
R^2	0.19	0.24	0.18	0.24	0.20	0.26	0.20	0.26
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Distance to No-Questions-Asked *d* and Stablecoin Convenience Yield After Nvidia Processor Releases. Table gives estimates from regressing a stablecoin's convenience yield on its estimated distance to NQA, $\hat{d}_{it}$. Observations are stablecoin by day and include all currencies for which we have convenience yield measures: USDT, USDC, BUSD, and DAI. Data restricted to three days after Nvidia launches new processors used for Ethereum mining. The dependent variable in the first two columns is the average convenience yield calculated across the three exchanges (the yield on lending bitcoin minus the yield on lending the stablecoin); columns (3) and (4) use the convenience yield from Exchange 1 which has data for USDT and DAI; columns (5) and (6) calculate the convenience yield using the implied repo rate on Bitcoin futures instead of the lending rate on Bitcoin; columns (7) and (8) calculate the convenience yield using the 1-month overnight-indexed swap rate instead of the implied repo rate or Bitcoin lending rate. BTC Basis is the Bitcoin basis as calculated using the generic front-month CME Bitcoin future and the CME Bitcoin index price. Average term is the average lending term for the stablecoin in days, and is available only from Exchange 1. R^2 is within-R^2. t-statistics are reported in parentheses using robust standard errors, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Online Appendix

A.1 Proposition 1. $\frac{\partial(CY)}{\partial d} < 0$

First, expand the convenience yield equation:

$$\begin{aligned}\text{Convenience Yield}_t &= R_t^f - R_t^d \\ &= R_t^f - \frac{1}{P_t(d)} \\ &= R_t^f - \frac{D_t^R(d)}{V_t(d)[1-N(h_D+\sigma)] + (1+r_f)^{-1} D_t^R(d) N(h_D)}\end{aligned}$$

We want to show that $\frac{\partial(CY)}{\partial d} = \frac{\partial}{\partial d}\left(\frac{-D_t^R(d)}{V_t(d)[1-N(h_D+\sigma)]+(1+r_f)^{-1}D_t^R(d)N(h_D)}\right) < 0$.

For simplicity call $D_t^R(d) = D(d)$, $V_t(d) = V(d)$. Then by the quotient rule:

$$\begin{aligned}\frac{\partial(CY)}{\partial d} =& \frac{D(d)\left(\frac{D'(d)N(h_D)}{1+r_f} + \frac{D(d)h'_D N'(h_D)}{1+r_f} - V(d)h'_D N'(h_D+\sigma) + V'(d)[1-N(h_D+\sigma)]\right)}{\left(\frac{D(d)N(h_D)}{1+r_f} + V(d)[1-N(h_D+\sigma)]\right)^2} \\ &- \frac{D'(d)}{\frac{D(d)N(h_D)}{1+r_f} + V(d)[1-N(h_D+\sigma)]} \\ =& D(d)\left(\frac{D'(d)N(h_D)}{1+r_f} + \frac{D(d)h'_D N'(h_D)}{1+r_f} - V(d)h'_D N'(h_D+\sigma) + V'(d)[1-N(h_D+\sigma)]\right) \\ &- D'(d)\left(\frac{D(d)N(h_D)}{1+r_f} + V(d)[1-N(h_D+\sigma)]\right) \\ =& D(d)\left(\underbrace{\frac{D(d)h'_D N'(h_D)}{1+r_f} - V(d)h'_D N'(h_D+\sigma)}_{=0} + V'(d)[1-N(h_D+\sigma)]\right) \\ &- D'(d)V(d)[1-N(h_D+\sigma)] \\ =& D(d)V'(d)[1-N(h_D+\sigma)] - D'(d)V(d)[1-N(h_D+\sigma)] \\ =& \underbrace{[1-N(h_D+\sigma)]}_{>0 \text{ if } h_D+\sigma<\infty}[D(d)V'(d) - D'(d)V(d)] < 0\end{aligned}$$

Thus, if $D(d)V'(d) - D'(d)V(d) < 0$, then $\frac{\partial(CY)}{\partial d} < 0$.

A.2 Data

Historical Data Banknote quote data from Weber (2021) is available at the following frequencies: Philadelphia (monthly 1830 to 1831; 1832 to 1858; data from *Bicknell's Reporter, Counterfeit Detector, General Prices Current* and *Van Court's Counterfeit Detector and* *banknote List*); New York (bimonthly, 1817 to 1849; monthly 1849 to 1857 with several gaps; data from the *Shipping & Commercial List, New-York Price Current* and *Thompson's banknote*); Cincinnati (February 1841, July 1845 to June 1847, February 1850, July 1854, from *Western Counterfeit Detector and banknote Table* and *Bradley & Co's Cincinnati Counterfeit Detector and banknote Reporter*); and, Cleveland (January, June, and September 1856 from the *Cleveland banknote Reporter*).

Global Financial Data describes the Moody's Municipal Bond 20-year Composite yield:

> Data from 1789 to 1856 is based upon individual bonds from different states. From 1789 to 1814, Massachusetts Notes (BSMANT) yielding 6% are used. In 1815 and 1816, South Carolina 6% Bonds (BSSC6S), the New York 6% Bonds (BSNY6S) from 1817 to April 1823 and from September 1843 to 1847, the New York Canal 5% Bonds due 1845 (BSNY5C45) from May 1823 to August 1843 and the New York State 5% Bonds due 1858 (BSNY558) from 1848 to 1856.

Global Financial Data describes the Moody's Corporate AAA Bond yield:

> Before 1857, data from individual corporate bonds is used. The Masonic Hall Association of Philadelphia 5% Loan is used from 1815 to 1827, the Chesapeake and Delaware Canal 6% Bonds is used from 1827 to 1831, the Schuylkill Navigation Co. 6% Bonds of 1840 is used from 1831 to 1837, the Baltimore and Ohio Railroad 6% Bonds is used from 1837 to 1842, New York, Lake Erie and Western Railroad Co. 7% 5th Mortgage Bonds of 1858 is used in 1842 and 1843, the Philadelphia Gas Works 6% Bonds of 1861 is used from 1843 to 1850 and the Baltimore and Ohio Railroad 6% Bonds of 1867 is used from 1850 to 1858 ...

Global Financial Data describes the relevant period of the 10-Year Treasury yield series:

> From 1790 to 1832, the government generally ran surpluses and redeemed its outstanding debt. By 1833, no debt was outstanding and no federal government bonds traded between 1833 and 1842. New York had the largest and most liquid debt during this period of time, so the New York 5% Canal Bonds due 1845 (BSNY5C45) is used between January 1833 and November 1842. New government bonds were introduced in 1843 and the federal government has had outstanding debt ever since. The United States 6% Bonds due 1862 (BGUSA662) are used between December 1842 and June 1848, the United States 6% Bonds of 1868 (BGUSA668) are used between July 1848 and July 1858, the United States 5% Bonds due 1874 (BGUSA574) are used between August 1858 and October 1860 ...

Bitcoin Basis We calculate the annualized Bitcoin basis by comparing the spot price of Bitcoin (S_t), measured by the CME's CF Bitcoin Reference Rate (BRR Index), and the generic next-month Bitcoin futures contract, F_t (BTC1 Curncy):

$$\text{Basis}_t = (F_t/S_t - 1) \times 12 \times 100$$

Ignoring financing costs, $\text{Basis}_t > 0$ implies the trader can profit by buying Bitcoin in the spot market and simultaneously selling Bitcoin futures. In practice, the trader would also need to finance the 50% margin that CME requires when trading Bitcoin futures.

Implied Repo Rate We calculate the annualized repo rate implied by future prices by comparing the spot price of Bitcoin (S_t), measured by the CME's CF Bitcoin Reference Rate (BRR Index), and the price of Bitcoin futures contract on date t for delivery at maturity m, F_t^m, with $d > 0$ days until delivery:

$$\text{Implied Repo Rate}_t^m = \frac{1}{N}\sum_m (F_t^m/S_t - 1) \times \frac{360}{d_t^m}$$

We then calculate the average implied repo rate on a given day by averaging the implied repo rate across all maturities.

A.3 Exclusion Restriction

The exclusion restriction of our instrumental approach requires that the instrument cannot be correlated with local growth prospects. The exclusion restriction is not directly testable, but we use falsification tests to show that banks in locations closer to the low-cost line were not larger and did not grow faster before the railroad was constructed.

Table A2 shows the correlation of the instrument, each bank's distance to the low-cost line, with the bank's level of bank assets and asset growth over the 15 years before 1849. None of the correlations are significant, indicating that banks closer to the low-cost line did not have larger assets or higher growth in the years before the railroad was constructed.

A.4 Other Reputation Development

Stablecoin Names The remainder of the top twenty stablecoins follows the same pattern: Liquidity USD (LUSD), Neutrino USD (USDN), HUSD, sUSD (SUSD), Alchemix USD (ALUSD), Gemini Dollar (GUSD), USDX (USDX), USDP Stablecoin (USDP), and sEUR (SEUR). Another large stablecoin, initially named "Paxos Standard" (PAX), renamed to "Pax Dollar" (*USD*P) as "the USDP ticker more easily identifies Pax Dollar as a US dollar-backed token."[28] Historically, banks also chose names to garner reputation: Friedman and Schwartz (1963) argue the 1930 bank run on the "Bank of United States," a commercial bank unaffiliated with the U.S. government, precipitated the wave of banking panics beginning in 1930. While simple, issuers' name choices aim directly at reducing a debt's distance to NQA.

Terms of Service Stablecoins can influence their d's through their contracts with their lenders. The contract is called the terms of service. It is tough to link the terms of service to d quantitatively. Still, the fact that terms of service are important for stablecoin issuers is clear in the evolution of Tether's terms of service over time.[29] Both the length of the terms of service has grown, and its Flesch–Kincaid reading level has increased over time.[30] If the terms of service were unimportant, it would be surprising to see such large changes over time.

The terms of service also describe stablecoins' reserves. Just like banks and money-market funds, concerns about the stablecoin's backing—the issuer's assets—can lead to a run on stablecoins. Thus, stablecoins also hold reserves to avoid runs and to maintain their redemption policies. Stablecoin issuers issue attestations to address these concerns about the reserve backing, and some also adjust the language in their terms of service.

In September 2019, a terms of service addendum for USDP and BUSD stated that they are backed by an equivalent amount of "US dollar deposits or US Treasury bonds".[31] This wording changed to a backing of "US dollar deposits or Debt Instruments" by October 2020 and to "US dollar deposits or Government Debt Instruments" by August 2021. The successive changes suggest there is substantial attention paid to the specific wording and details of the terms of service. Also, the NYAG investigation of Tether likely makes stablecoin issuers more circumspect about the details.

[28] See `https://paxos.com/2021/08/24/the-digital-dollar-that-always-equals-a-dollar-paxos-standard-pax-is-now-pax-dollar-usdp/`.

[29] See Figure A4.

[30] The Flesch–Kincaid reading level is based on a score that considers such factors as word and sentence length. An increase in the score indicates the terms of service have become harder to read.

[31] https://paxos.com/2019/03/29/usdp-terms-conditions/: The US Dollar Stablecoin Terms and Conditions are an addendum to the terms of service for USDP and BUSD.

A.5 Figures

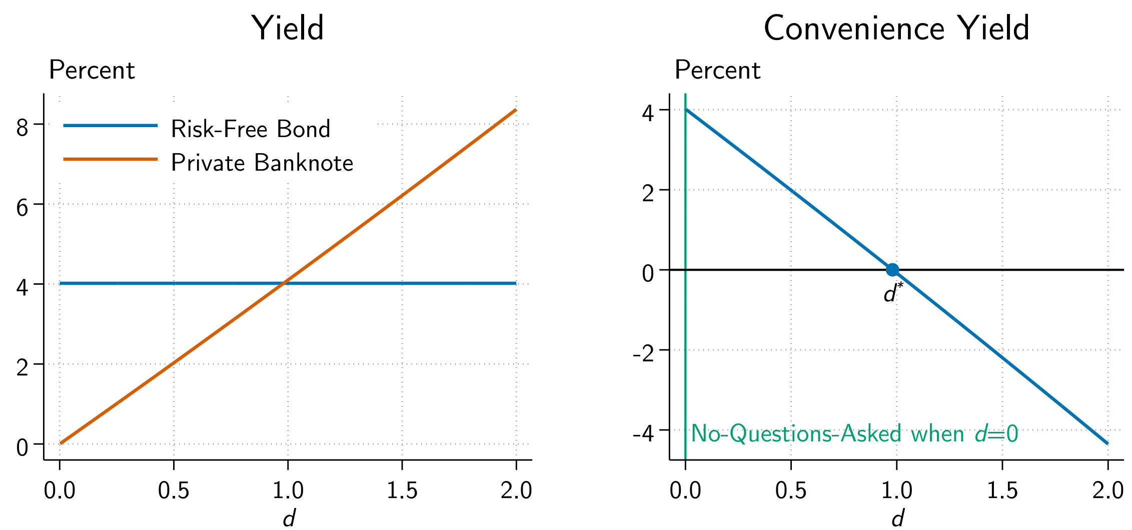

Figure A1: Model Intuition. Figure plots the yields on banknotes and risk-free bonds and assumes consumption follows a lognormal independent and identically distributed process so that the risk-free rate is $R_t^f = \left(\beta \exp\{-\gamma\mu_c + \frac{1}{2}\gamma^2\sigma_C^2\}\right)^{-1}$ where μ_C and σ_C describe the consumption process, and γ is coefficient of relative risk aversion. The right panel plots the convenience yield given in equation 5, which is the difference between the two yields on the left panel: Convenience $\text{Yield}_t = R_t^f - R_t^d$. Figure uses $\beta = 0.98, \mu_C = 0.01, \sigma_C = 0.02, \gamma = 2, \sigma = 0.2, V_t(d) = 100$, and $D_t^R(d) = 1$.

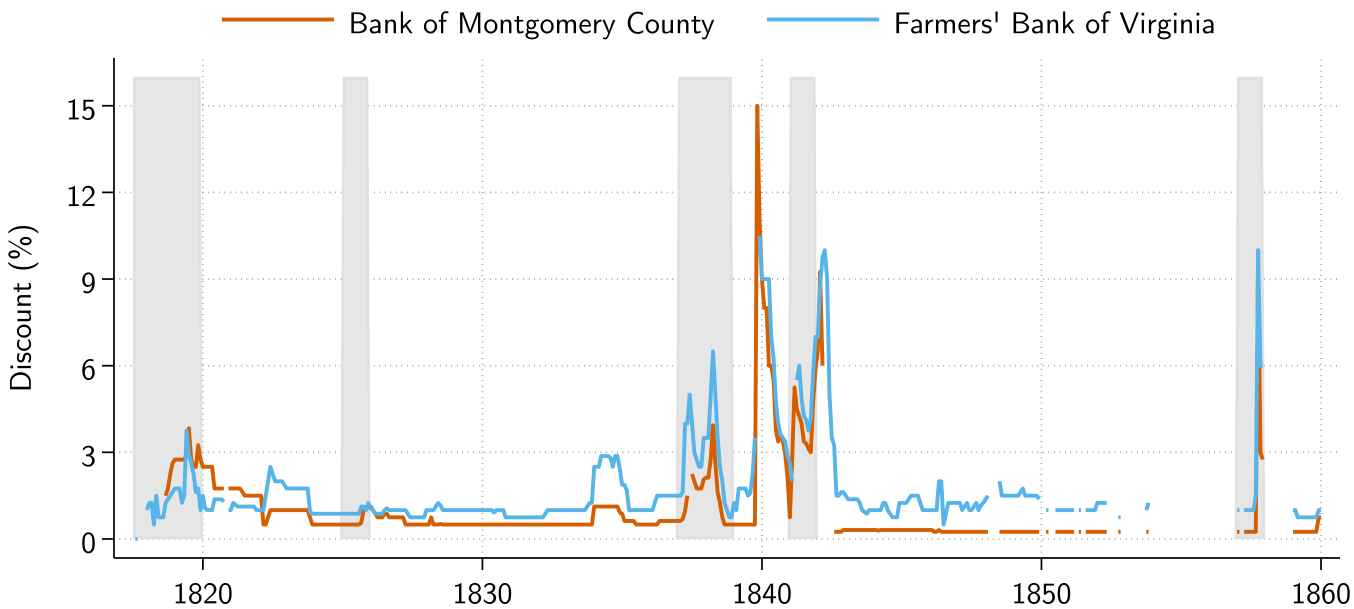

Figure A2: Banknote Discount Example. Figure plots New York discounts for two selected banks; shaded areas denote crises as given by Trebesch et al. (2021). Discounts are quotes relative to par: a bank with a 10% discount has a price of $\$1 \times (1 - 0.1) = \$0.90$.

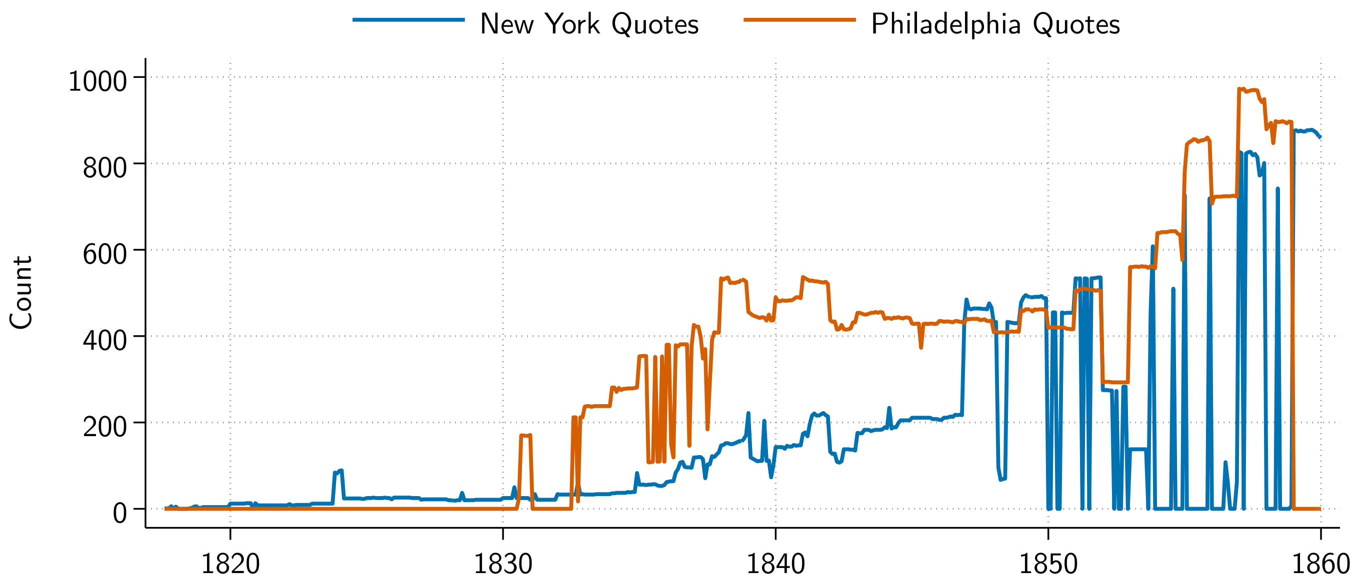

Figure A3: Banknote Count. Figure plots the number of individual banks with merged banknotes in our sample in each month.

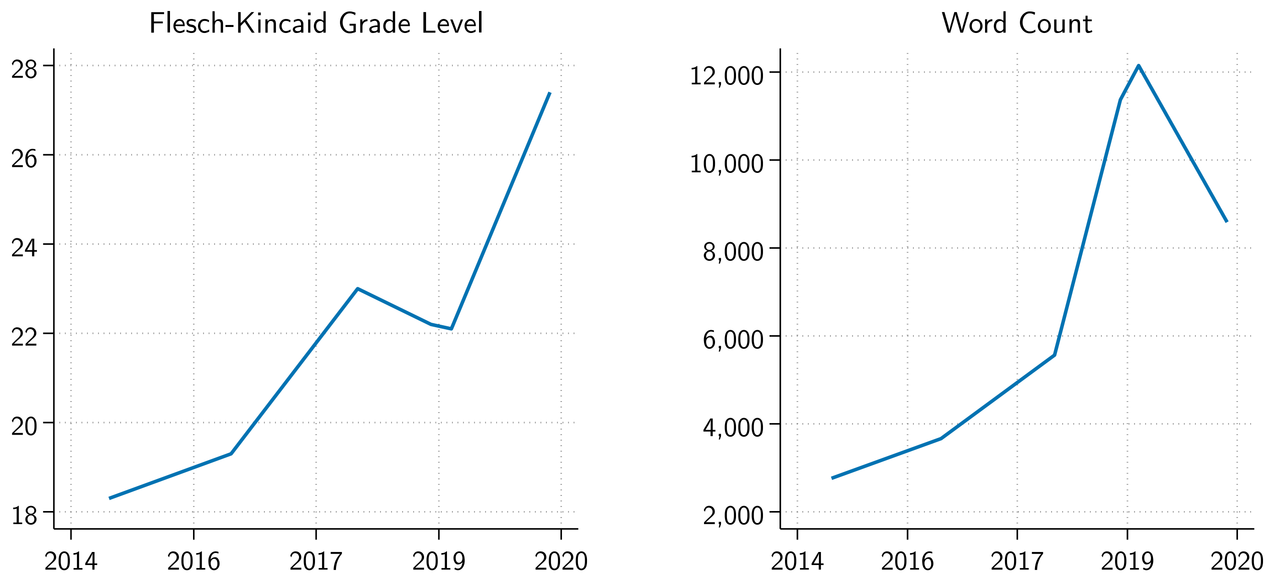

Figure A4: USDT Terms of Service Figure plots the Flesch-Kincaid grade level and word count of USDT's terms of service over time. We manually capture five distinct snapshots of the terms of service over time. The Flesch-Kincaid grade level measure estimates the years of schooling required to understand the text.

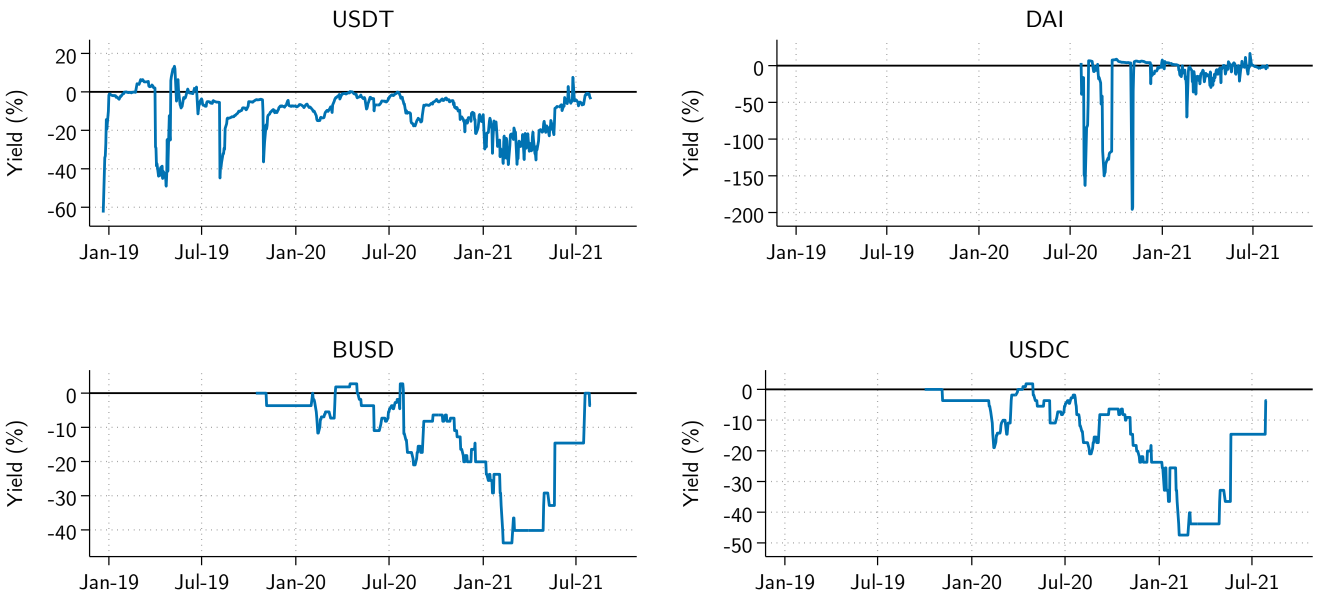

Figure A5: Stablecoin Convenience Yield Figure plots the convenience yield for each currency when averaged across all exchanges for which we have data, where the convenience yield is calculated using lending rates for the stablecoin and Bitcoin. Convenience yield is $y^{BTC} - y^{Stablecoin}$.

A.6 Tables

	Mean	ρ
Benchmark Estimate		
New York Quotes	0.88	1.00***
Philadelphia Quotes	0.30	1.00***
Commercial Paper r_f		
New York Quotes	0.30	0.84***
Philadelphia Quotes	0.21	0.87***
Fixed 5% r_f		
New York Quotes	0.73	0.99***
Philadelphia Quotes	0.31	0.99***
Fixed 9% r_f		
New York Quotes	0.41	0.98***
Philadelphia Quotes	0.17	0.99***
Price σ		
New York Quotes	0.93	0.42***
Philadelphia Quotes	0.46	0.91***

Table A1: Banknote Distance to No-Questions-Asked Estimates with Alternative Assumptions. Table presents the mean d and correlation ρ of the estimation's value-weighted aggregate d with the benchmark estimate d for the same dataset (New York or Philadelphia). d units is years. Value-weights are calculated using lagged circulation shares. The benchmark estimate uses the Global Financial Data's 10-Year Treasury rate as the risk-free rate and the annualized volatility of monthly asset growth over the previous year. The commercial paper estimate uses the commercial paper rate reported by Smith and Lole (1935) based on Bigelow (1862) and available from Global Financial Data for the period beginning in December 1835. The fixed rate estimates use a fixed risk-free rate of 5% (roughly the average Treasury yield over the period 1817 to 1860) and 9% (roughly the average commercial paper rate in the sample available from Bigelow (1862). The price σ estimate uses annualized price volatility of the bank notes as implied by monthly changes in discounts over the previous twelve months. Correlation significance reported where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Over Prior 15 Years			
	Bank Assets	Asset Growth	Bank Assets	Asset Growth
Distance to Low-Cost Line	0.072	0.068		
	(0.39)	(0.42)		
Within 30 Miles of Low-Cost Line			−0.034	−0.052
			(0.68)	(0.54)
N	143	143	143	143

Table A2: Correlation of Distance to Low-Cost Line with Local Growth Prospects. Table presents the correlation of the distance to the low-cost line and bank asset level, asset growth, and relative asset growth over the prior 15 years. P-values reported in parentheses where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Avg. Across Exchanges		Exchange 1		Implied Repo Rate		OIS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{d}_{it}$	-8.59^{***}	-10.88^{***}	-10.38^{***}	-10.69^{***}	-10.85^{***}	-11.17^{***}	-10.91^{***}	-11.23^{***}
	(−3.48)	(−3.69)	(−3.49)	(−3.64)	(−3.65)	(−3.82)	(−3.68)	(−3.85)
Bitcoin Basis		-0.07^{***}		-0.06^{***}		−0.03		-0.05^{**}
		(−3.16)		(−2.84)		(−1.32)		(−2.34)
Bitcoin Return		−0.08		0.11		0.06		0.07
		(−0.61)		(0.89)		(0.56)		(0.64)
Average Term		-0.12^{***}		-0.10^{***}		-0.09^{***}		-0.09^{***}
		(−3.42)		(−3.38)		(−3.07)		(−3.05)
OIS−Tbill		−4.51		−7.47		−12.73		−11.52
		(−0.29)		(−0.48)		(−0.90)		(−0.82)
ln(Volume)		-2.50^{***}		-2.95^{***}		-3.63^{***}		-3.60^{***}
		(−2.89)		(−3.26)		(−4.16)		(−4.14)
N	1,889	933	933	933	933	933	933	933
R^2	0.24	0.25	0.23	0.26	0.26	0.28	0.26	0.29
Coin Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A3: Distance to No-Questions-Asked $\boldsymbol{d}$ and Stablecoin Convenience Yield with Alternative Convenience Yield Measures and Additional Controls. Table gives estimates from regressing a stablecoin's convenience yield on its estimated distance to NQA, $\hat{d}_{it}$. Observations are stablecoin by day and include all currencies for which we have convenience yield measures: USDT, USDC, BUSD, and DAI. The dependent variable in the first two columns is the average convenience yield calculated across the three exchanges (the yield on lending bitcoin minus the yield on lending the stablecoin); columns (3) and (4) use the convenience yield from Exchange 1 which has data for USDT and DAI; columns (5) and (6) calculate the convenience yield using the implied repo rate on Bitcoin futures instead of the lending rate on Bitcoin; columns (7) and (8) calculate the convenience yield using the 1-month overnight-indexed swap rate instead of the implied repo rate or Bitcoin lending rate. BTC Basis is the Bitcoin basis as calculated using the generic front-month CME Bitcoin future and the CME Bitcoin index price. Average term is the average lending term for the stablecoin in days, and is available only from Exchange 1. R^2 is within-R^2. T-statistics are reported in parentheses using Driscoll and Kraay (1998) standard errors with a maximum of 5 lags are reported in parentheses, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Release Date	Hash Rate Avg.	Cumulative Avg.
GeForce RTX 2060	1/15/19	30.5	30.5
GeForce GTX 1660 Ti	2/21/19	29.6	30.1
GeForce GTX 1660	3/14/19	22.0	27.4
GeForce GTX 1650	4/23/19		27.4
GeForce RTX 2060 Super	7/9/19	39.5	30.4
GeForce RTX 2070 Super	7/9/19	40.5	32.4
GeForce RTX 2080 Super	7/23/19	41.0	33.9
GeForce GTX 1660 Super	10/29/19	29.7	33.3
GeForce GTX 1650 Super	11/22/19	31.0	33.0
GeForce RTX 2060	1/10/20	30.5	32.7
GeForce GTX 1650	4/3/20		32.7
GeForce GTX 1650	6/18/20		32.7
GeForce RTX 3080	9/17/20	94.8	38.9
GeForce RTX 3090	9/24/20	117.0	46.0
GeForce RTX 3070	10/29/20	60.1	47.2
GeForce RTX 3060 Ti	12/2/20	59.1	48.1
CMP HX	2/18/21	86.0	50.8
GeForce RTX 3060	2/25/21	41.5	50.2
GeForce RTX 3080 Ti	6/3/21	85.0	52.4
GeForce RTX 3070 Ti	6/10/21	55.1	52.5
GeForce RTX 3060	9/1/21	41.5	51.9

Table A4: Nvidia GPU Release Dates. Table gives the release dates and hash rates for Nvidia GPUs. Data is sorted by release date. The average hash rate is the average of available hash rates collected from WhatToMine, 2CryptoCalc, and Nvidia. Hash rates are mining rates for Ethash in Mh/s. Cumulative Average is the rolling average of available average hash rates.