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Regulation and the funding of new ventures*

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Abstract

We examine the effects of regulation and the motives that underpin it. The development of the crypto sector offers a unique setting due to the absence of incumbents, the lack of pre-existing rules and the fact that governments regulated the sector holistically. We construct a comprehensive measure of regulatory activity at the state-month level for the United States based on state laws affecting the crypto sector and find that both consumers' and entrepreneurs' pressure drives regulation, in line with theories of economic regulation. We also find a positive association between regulation and venture capital funding in financial hubs. A detailed analysis of the New York's BitLicense sheds light on the mechanism: regulation reduced information asymmetries, enhancing funding for start-ups. Overall, our results highlight the complex motives behind regulation, which can address genuine market failures even when driven by the interest of competing groups.

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"The state – the machinery and power of the state – is a potential resource or threat to every industry in the society. With its power to prohibit or compel, to take or give money, the state can and does selectively help or hurt a vast number of industries."

George J Stigler (1971)

1 Introduction

Why do governments regulate? On the one hand, governments could introduce regulation to protect citizens and consumers' interests. On the other hand, regulation could act as a product supplied by the government and bought by regulated firms (Stigler, 1971). Under the latter interpretation, there are two relevant groups: a cohesive minority (the regulated firms), which is able to extract regulation protecting it from the threat of entry of new competitors; and a diffused majority (the consumers), which suffers harm as it shoulders the regulatory costs. In this paper, we study the relative importance of these interest groups when it comes to regulating new industries. Nascent industries, which by definition lack a cohesive incumbent minority, can help isolate what pushes regulators to intervene (Peltzman, 2021; Becker, 1983).

The birth of the crypto industry in the late 2000s in the U.S. offers an ideal laboratory to examine these issues. First, crypto develops from scratch around 2009, and there are no obvious reasons why crypto activity should be more concentrated in one state rather than in others. Importantly, there are –by definition–no pre-existing rules that may confound the effects of any new regulatory framework subsequently introduced.[1] We hence avoid common pitfalls associated with the regulation of established sectors, where path dependence can significantly influence outcomes. Second, the roles of the interest groups are clear: on the one hand, as there are no incumbents, an increase in

[1] For more details on the substantial lack of regulation see Biais et al. 2023.

barriers to entry to protect a dominant position is unlikely to be the motivation driving regulation;[2] for consumers, on the other hand, regulation could protect them from scams and fraudulent activities, which can potentially be pervasive at the early stages of a new industry. Finally, since public authorities had to build a regulatory framework for the crypto industry as a whole, rather than focusing on specific aspects or processes, we are able to assess the effects of regulation holistically, ie by taking into account the entire regulatory *environment*.[3]

To study the drivers of crypto regulation, we compile detailed information on state laws and regulations impacting the crypto sector across all U.S. states, sorting them into 15 different categories or *pillars*.[4] Our scope is intentionally broad, as we aim to capture the overall regulation level of crypto activities in each state. The pillars include regulation on whether crypto platforms must comply with money transmission law and if they require a general/specific license; if crypto-related earnings are taxable or tax exempt; whether state banks can act as crypto custodians; or whether contracts signed using the blockchain are enforceable by law. Using this information, we construct an index of regulatory activity at the state-month level from January 2010 to December 2022. We call this index the Crypto Regulation Index or *CRegIn* in short.

First, we show that regulation at the state level is consistent with pressure coming from two distinct groups: consumers and funding actors. Using data from the Consumer Financial Protection Bureau and the U.S./ Senate Lobbying Disclosure Act (LDA) Reports database, we show that past consumer complaints as well as cryptocurrency-related lobbying are associated with more regulation in a state. Consistent with the

[2] Indeed, established players in the financial industry remain relatively unconcerned about potential competition from crypto firms even 15 years later.

[3] Cong et al. 2023b document the effect of regulation on crypto exchanges. Conversely, our paper documents the holistic effect of regulation and doesn't focus on the regulatory framework of a specific player in the market.

[4] Crypto-related activities are mostly regulated at the state level, with a historical lack of substantial federal regulation.

theory of economic regulation, we show that the relative strength of the different competing groups is an important determinant of regulatory activity. Consumer complaints do not impact regulation differently in states with a more developed financial sector. The effect of lobbying activity on regulation, however, is four times larger in financial hubs relative to non-financial hubs. Lobbying groups focus their attention on financially stronger states, where new ventures are likelier to rip benefits, hence motivating our analysis into the effects of regulation on venture capital (VC) funding.

Second, we analyse the effects of crypto regulation on the VC investment in new ventures. VC plays a crucial role in financing young innovative firms, and helping them commercialise their products (Da Rin et al., 2013; Comin and Nanda, 2019).[5] It is hence important to determine the consequences of regulation on these types of investments. Using *CRegIn* as a proxy for the regulatory environment, we find that regulation is positively and significantly correlated with VC funding, but that the effect is entirely driven by financial hubs: both capital invested and the number of deals are associated with a more comprehensive regulatory framework in those states. In particular, a one standard deviation increase in the index is associated with an increase in capital raised in a financial hub by around 30%. States with a less developed financial sector do not display such a correlation. Therefore, industry lobbying in financial hubs for regulation proved successful in increasing VC investment into crypto ventures.

To understand the causal mechanism behind the association, we zoom in on a large change in the comprehensiveness of regulation in a financial hub. In particular, we focus on the introduction in 2015 of regulation 23 NYCRR Part 200, commonly known as the

[5] VC bridges the gap between the earliest stages of start-ups, when there is more uncertainty around an idea and its potential returns, and more mature firms that can rely on bank loans or capital markets. Firms funded by VC achieve greater scale, are responsible for a greater share of employment and are less likely to fail, especially in the first years of their life (Puri and Zarutskie, 2012).

BitLicense, in the state of New York. Using granular firm-level data, we find evidence consistent with the BitLicense decreasing information asymmetries, making it easier for VC firms to filter and select projects.[6]

We provide evidence of a decrease in information asymmetries by looking both at firms that received funding as well as at the investors that provided those funds. From the perspective of firms, we observe a substantial increase in funding for young firms, start-ups, and firms in sectors characterized by limited pledgeable collateral. Extensive literature indicates that information asymmetries are more pronounced for young and start-up firms (Morellec and Schürhoff, 2011; Conti et al., 2013), as entrepreneurs have better knowledge of the quality of their risky project compared to potential investors. Firms with less tangible assets that could be pledged as collateral as, for example, software firms (Goyal and Wang, 2013; Aboody and Lev, 2000) are also harder to asses. We add to this literature in the context of VC funding for crypto firms. From the perspective of investors, we find that foreign investors, those with less experience in crypto firms, and the ones with fewer investment professionals invest more capital in crypto start-ups following the introduction of the BitLicense.

Our results reveal that while different pressure groups were successful in lobbying states to regulate the industry, they did so in a way that mitigated a market failure: information asymmetries between firms and VC investors. Overall, the efforts of both consumers and entrepreneurs are associated with additional regulation of the industry, which leads to more VC investment in those states that have a stronger financial sector.

Contributions and related literature. The first contribution of this article is the production of the index on regulatory comprehensiveness (CRegIn), which we are making

[6] Our results are robust to placebo tests and alternative definitions of the control group (falsification tests and using New York fintechs as control).

publicly available to other researchers. Researchers can use the index, for example, to understand how regulatory comprehensiveness on crypto varies state to state.

We contribute to the literature on the theories of economic regulation (Kroszner and Strahan, 1999; Peltzman, 2021) by providing evidence consistent with the pressure from two distinct groups (consumers and entrepreneurs) successfully influencing regulation. Furthermore, we show that lobbying efforts were higher in financial hubs, where entrepreneurs benefited more from VC investment.

Our article also contributes to the literature showing that regulation can have a positive effect on VC investment. Some papers study the effect on individual firms of entering regulator-designed programs, such as regulatory sandboxes (Cornelli et al., 2024), or receiving a government grant (Howell, 2017). These studies find that firms that benefited directly from grants or access to a sandbox raised significantly more venture capital than comparable firms that did not benefit from these programs. Similar evidence holds for business accelerators or incubators (Gonzalez-Uribe and Leatherbee, 2018; Yu, 2020), which operate either as public-private initiatives or as industry-led programs. Regulatory sandboxes, grants, and business accelerators all act as quality certifications that allow potential venture capitalists to better asses the quality and potential of a project.

Other strands of the literature show that regulation as a whole can encourage VC investment and consequently innovation. Kim et al. 2018 shows that the passage of the European Orphan Drug Act, aimed at encouraging investment for the discovery of new treatments for rare diseases, was positively associated with VC investment. Useche 2014 and Hoenig and Henkel 2015 find that patent regulation encourages both innovation and VC investment. Cong and He 2019 highlight how the crypto-industry enlarges the contracting space through smart contracts. We contribute to this literature by showing that the effects hold for nascent industries, underscoring that regulatory attitudes as summarized by our index, can have a positive impact in VC investment.

This paper has implications for the policy debate, especially as several jurisdictions are introducing new regulation for crypto assets, like the Markets in Crypto-Assets Regulation (MiCA) in the European Union, or for regulation targeting artificial intelligence. Our findings underscore how regulation can encourage the development of new firms. Regulators concerned about increasing red tape costs for existing firms should also consider the positive effects for younger firms that regulation can have in promoting VC investment.

The rest of the paper is structured as follows: Section 2 describes the conceptual framework guiding our analysis; Section 3 presents the data and the index construction; Section 4 analyses the drivers and the effects of crypto regulation, with Section 4.1 analysing the different pressure groups; and Section 4.2 analysing the effects of regulation; Section 5 discusses the analysis of the BitLicense; Section 6 concludes.

2 Conceptual framework

This section explains the conceptual framework that we use to study the emergence of regulation and its effects.

Following Stigler 1971, regulation can be seen as a product supplied by governments and "purchased" by regulated firms. Under this view, a cohesive minority (regulated firms) seek to secure regulations that protect them from new competitors, benefiting significantly at the expense of the diffused majority (consumers). Consumers suffer minimal harm as the costs are spread among many, while the limited number of firms in the market enjoy substantial benefits. Different types of firms and consumers have the ability to organize into pressure groups (Peltzman, 1976; Becker, 1983). The political equilibrium that gives rise to regulation depends on each groups' size and efficiency in exerting pressure.

In a nascent industry, which by definition lacks a cohesive minority of incumbent firms, three main groups attempt to shape regulation: entrepreneurs, investors and consumers. Entrepreneurs develop new products for the market and rely on capital from investors to fund their projects. They may pressure the government to legitimize the new industry, hence facilitating investment flows and consumer confidence. Investors face multiple potential entrepreneurs and may suffer from information asymmetries. They are likely to seek regulations that help them identify successful entrepreneurs, making their investment decisions easier. Hence, the interests of these two groups are likely to be aligned, at least in the initial period in which the industry develops. In more mature industries, established firms may seek to increase entry barriers for potential competitors, which decreases investment into the sector and harms new investors. Finally, consumers pressure regulators for adequate consumer protection, aiming to ensure that products are trustworthy.

We therefore expect the regulation of a nascent industry to be influenced by the interactions of these three types of agents. Their influence, however, is not similar in all states: while consumers are diffused across all states and likely exert uniform pressure on the government, entrepreneurs and investors are concentrated in certain states and exert more pressure where they have a higher relative weight.

We hence test two main hypotheses in our paper. First, we examine whether the initial regulation of the crypto industry is influenced by consumers and firms. Second, we explore the impact of regulation on the interaction among investors and entrepreneurs using the introduction of a specific regulatory in the state of New York.

3 Variable construction and descriptive statistics

3.1 Building a state index of regulatory comprehensiveness

We create a comprehensive and detailed database of U.S. crypto-related state regulation, from January 2010 to December 2022. Our focus is intentionally broad as we aim to capture overall regulatory attitudes toward crypto in each state. Therefore, we look for laws passed in 15 wide-ranging categories, which we call *pillars*, covering whether: the state's money transmission regulation applies to crypto-assets; there is a license required to trade and exchange money and it applies to transactions conducted with crypto-assets; the state additionally requires a specific license for conducting transactions with crypto-assets; such license requires a third-party audit of the systems; there is regulation covering crypto-ATMs; there is a sandbox program in place; income from crypto-related activities is explicitly taxable or is tax-exempt; sales of crypto-related assets are taxable or tax-exempt; anti-money laundering and know-your-customer legislation applies to crypto-related activities; state banks can act as custodians of crypto-assets; banks acting as custodians have specific liquidity provisions for those crypto-assets; the public sector accepts payments in crypto-currencies; and whether transactions in a blockchain are legally recognized in the state.

Our methodology follows closely the one developed by Babina et al. (2022) in the context of open banking. For each of our 15 pillars, we conduct Google searches for mentions of laws that relate to crypto applications and then refer to the original texts. We prioritize official government or policy documents, and when those are not available, we use documents by law firms, industry participants, and academia.[7] We retrieve from the passed bill the date when the law was approved and the date when it came

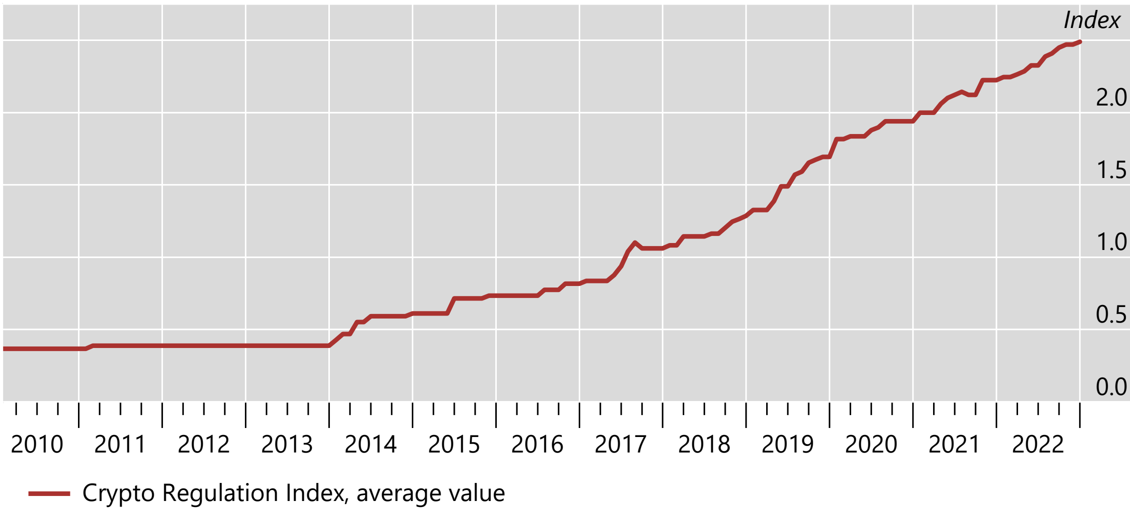
[7] Like, for example, the Stevens Center at The Wharton in the University of Pennsylvania.

into effect.[8] Each author conducted these searches independently and we then jointly reconciled any discrepancies.

The result is a monthly panel from January 2010 to December 2022 for each state, where each of our 15 pillars is a categorical variable that takes the value of one in the months where a law in such pillar is in force. We then sum across all 15 pillars to obtain the index for each month in each state. We denote this index the Crypto Regulation Index, or *CRegIn* in short.[9]

The average state passes 1.6 laws, with some states passing as many as four. Each year, around 6.3 laws are passed related to crypto regulation. Figure 1 shows CRegIn's evolution. On average, regulatory comprehensiveness across states increased over time.

Figure 1: **The Crypto Regulation Index (CRegIn)**



NOTE: The figure shows the cross-state simple average of the CRegIn.
SOURCE: Authors' calculations.

There could be two concerns regarding what our index captures: first, it could be that states that had higher levels of VC investment before 2010 (that is, before we

[8] We use the websites law.justia.com, legiscan.com, and casetext.com.

[9] Note that our index does not measure the clarity of the laws being passed, only whether there are additional rules in one state that firms engaging in crypto activities need to abide. Hence we cannot comment on whether the laws increase regulatory clarity.

observe the first states passing crypto specific regulation) were more likely to regulate the crypto sector to encourage VC investment. However, the correlation between the logarithm of overall VC investment in the period prior to regulation (2000–2009) and various measures of the index, such as the average index over 2010–2022, or the index by December 2022, is very low (around 0.16) and not statistically significant. This low correlation suggests that our index captures something other than pre-regulation VC funding. Another concern could be that our index is too broad and that, instead of capturing the comprehensiveness of crypto regulation, it captures general state attitudes or state-specific policies affecting economic activities. We therefore contrast CRegIn with the Fraser Index of economic freedom (see Fraser Institute Economic Freedom). The pairwise correlation of our CRegIn with the overall state-level Fraser Index of economic freedom is low (less than 0.2 in absolute value). We find an even smaller correlation when comparing CRegIn to the Fraser Index sub-components. This suggests that our CRegIn is unlikely to be confounded by state-specific policies affecting freedom of conducting generic economic activity.

3.2 Data on private market deals

Data on private market deals come from PitchBook Data Inc. PitchBook is one of the leading sources for private market deal-level data and it has been extensively used in VC research (Cornelli et al., 2024; Ewens et al., 2022; Gompers et al., 2021).[10] The sample for our analysis covers more than 3,600 funding transactions in crypto related firms between January 2010 and December 2022 (see Figure 2).[11] Of these, more than

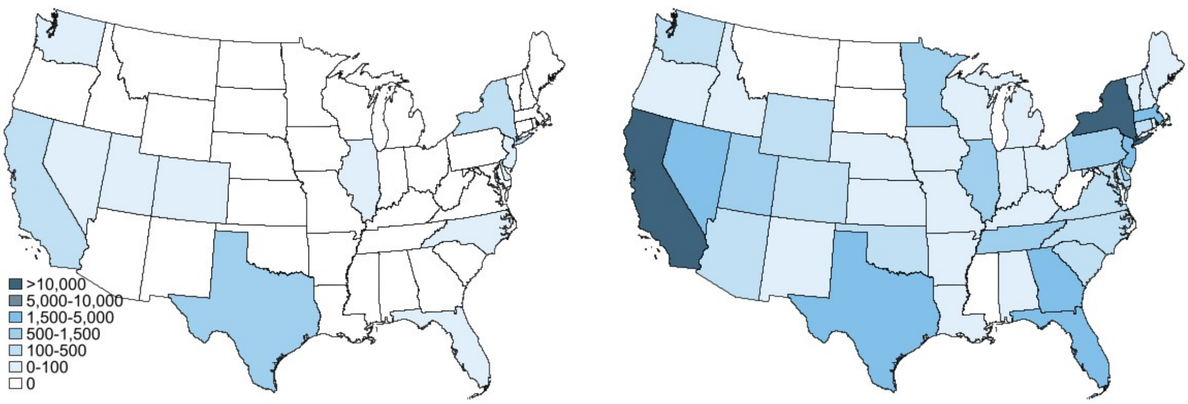
[10] The deals and investment we focus on are made by professionals, denominated in U.S. dollars and with the objective to finance a project to develop a product. The deals involve a company looking for funding from corporate investors, not retail individuals. We completely abstract from initial coin offerings, which have often been promoted to unsophisticated retail investors and have been a fertile ground for scams (Morris, 2017; Phua et al., 2022; Cong et al., 2023a, 2025).

[11] PitchBook provides its own categorization of cryptocurrency companies into specific industry verticals or segments. These segments consist of firms that deliver similar products and services

90% are VC transactions, with the remaining being private equity, private debt and mergers and acquisition deals. Over this period more than 2,000 crypto-related firms domiciled in the United States raised capital. For each deal, PitchBook collects granular information on the amount raised, the exact date of the deal, the type and purpose of the deal, information on education and gender of the CEO, the age of the firm, the business sector in which it operates, the business status, the firm's geographical location, and information on the investors.

Figure 2: **Investment in crypto firms increased remarkably from 2012 to 2022**

(a) Investment up to 2012 (b) Investment up to 2022



Note: The graph shows the cumulative capital invested in crypto deals since 2010, in millions of U.S. dollars, excluding Alaska, Hawaii, and Mississippi, by 2012 (left) and 2022 (right).
Source: PitchBook Data Inc; U.S. Census Bureau; authors' calculations.

Leveraging this information we derive three indicator variables that we use to identify firms that are more affected by information asymmetries: $\mathbb{1}\left[\text{Young}_{i,t}\right]$ is an indicator variable that takes value one when firm i is less than two years old; $\mathbb{1}\left[\text{Start-up}_{i,t}\right]$, is an indicator variable that takes value one in the year a firm is founded; $\mathbb{1}\left[\text{Low-collateral}_{i}\right]$, is an indicator variable that takes value one if a firm is active in an industry whose asset tangibility, and consequently collateral pledgeability, is traditionally limited. Following

within a specialized market. According to PitchBook, verticals are structured to cut across various industries, meaning a single vertical can include companies from multiple industries. For our analysis, we examine all investments classified under cryptocurrency/blockchain.

Aboody and Lev (2000) and Trester (1998) we consider firms for which the primary industry group is software as low-collateral. Furthermore, we derive $\mathbb{1}\left[\text{Survival}_i\right]$ which is an indicator variable that takes value zero if by October 2023 the firm had gone bankrupt, and value one if it is still in business.

Finally, we derive three indicator variables that we use to identify investors that are more affected by information asymmetries: $\mathbb{1}\left[\text{Foreign investor}_j\right]$ is and indicator variable that takes value one if the investor is not headquartered in the United States; $\mathbb{1}\left[\text{Non-specialist investor}_j\right]$ is an indicator variable that takes value one if cryptocurrency is a sector that the firm had not traditionally targeted; $\mathbb{1}\left[\text{Small investment firm}_j\right]$ is and indicator variable that takes value one when the investor has less than five investment professionals.

3.3 Data on consumer complaints and lobbying

We collect data on consumer complaints related to virtual coins from the Consumer Complaints Database managed by the Consumer Financial Protection Bureau (CFPB). We use the complaints dataset as a proxy for consumer demand for legislation. Several factors can influence consumers' demand, such as quality assurance, clarity on rights, or protection against fraud. We aggregate the data at the state-month-year level to construct the number of complaints variable.

The data on the amount spent on lobbying on issues related to cryptocurrencies come from the U.S./ Senate Lobbying Disclosure Act (LDA) Reports database. Specifically, we search reports with specific issues containing at least one of the following keywords: bitcoin, blockchain, crypto, cryptocurrency, cryptocurrencies, decentralized finance, DeFi, digital asset, digital assets, digital currency, digital currencies and ethereum. The resulting data contain information on the amount spent by each firm on lobbying on issues pertaining cryptocurrencies together with information on the firms' headquartered state. We aggregate these data at the state-month-year level to obtain a measure of the interest in cryptocurrency regulation from the private sector.[12]

3.4 Data on the finance and insurance sectoral GDP

The data on sectoral GDP for the finance and insurance sector comes from the Bureau of Economic Analysis. We use these data to identify financial hub states. Specifically, for each state we compute the total GDP for the finance and insurance sector for the period 2000–09 (right before crypto trading picked up), and we use this measure to determine whether a state belongs to the top-half/bottom-half, or the top-tercile/bottom-tercile of the finance GDP distribution.

Table 1 shows the descriptive statistics. Panel A provides summary statistics at the state-month-year level for the pressure group analysis. On average there is one complaint every two million inhabitants and USD 0.13 per capita is spent on lobbying on crypto related issues. Panel B provides summary statistics at the state-month-year level for the state-level analysis on the impact of regulation on private market deals. There is an average of one deal per month in a state, and the average monthly capital raised is USD 4.17 millions, although there is a considerable range (some states do not raise capital in some months, while others raise more than USD 100 millions in a single month). Panel C provides the summary statistics at the firm level at the time of the deal. The average firm in our sample is less than one year old when making a deal, its CEO is most-often male, and 73% of the firms in our sample remain operational by October 2023. Finally, Panel D shows summary statistics at the investor-firm level. The average investor is

[12] The implicit assumption here is that state-level lobbying is correlated with federal lobbying. Unlike federal lobbying, disclosure of state-level lobbying is not regulated across all 50 states. Therefore, to the best of our knowledge there is no database enabling us to measure state-level lobbying consistently and directly.

headquartered in the United States, does not specialise in the crypto industry and has more than five employees.

Table 1: Descriptive statistics

Panel A: pressure groups analysis					
	No obs	Mean	St dev	Min	Max
CRegIn	6,552	1.21	1.42	0	7
Consumer complaints	6,552	0.47	1.03	0	13.48
Lobbying	6,552	0.13	2.56	0	92.28

NOTE: The sample includes 49 states for the period 2010–22. *CRegIn* refers to the Cryptocurrency Regulation Index. *Consumer complaints* corresponds to the number of consumer complaints related to cryptocurrencies per million people . *Lobbying* corresponds to the dollar amount per capita spent on lobbying on issues related to cryptocurrencies.

Panel B: state-level analysis					
	No obs	Mean	St dev	Min	Max
Deals					
Capital raised, in USD mn	7,644	4.17	23.31	0	196.76
Number	7,644	0.73	3.31	0	74
CRegIn	7,644	1.04	1.38	0	7

NOTE: The sample includes 49 states for the period 2010–22. *Capital raised* is winsorised at the 1st and 99th percentiles. *CRegIn* refers to the Cryptocurrecy Stringency Index.

Panel C: firm-level analysis					
	No obs	Mean	St dev	Min	Max
Cumulative capital raised, in USD mn	2,584	4.18	18.15	0	262
Firm age	2,584	0.85	1.91	0	7
CEO male, (0/1)	2,584	0.97	0.16	...	...
CRegIn	2,584	0.59	1.34	0	4
Deal number	2,584	1.21	1.26	0	5
Young, (0/1)	2,584	0.62	0.48	...	...
Startup, (0/1)	2,584	0.18	0.39	...	...
Low-collateral, (0/1)	2,584	0.80	0.40	...	...
Survival, (0/1)	2,584	0.73	0.44	...	...

NOTE: The sample includes quarterly data for 152 firms around the approval of the New York DFS BitLicense ie Sep 2013 to Jun 2017. *Cumulative capital raised* is winsorised at the 2nd and 98th percentiles.

Panel D: investor-firm-level analysis					
	No obs	Mean	St dev	Min	Max
Cumulative capital invested, in USD mn	21,968	0.56	1.98	0	48.37
Foreign investor, (0/1)	21,935	0.21	0.45	...	...
Non-specialist investor, (0/1)	21,935	0.68	0.47	...	...
Small investment firm, (0/1)	21,968	0.41	0.49	...	...

NOTE: The sample includes quarterly data for 942 investors and 142 firms around the approval of the New York DFS BitLicense ie Sep 2013 to Jun 2017. Foreign investor refers to investors headquartered outside of the U.S. Non-specialist investor refers to investors whose main sector is not the crypto sector, and Small investment firm refers to VC firms with less than five investment professionals.

4 The drivers and state-level effects of crypto regulation

4.1 Pressure groups and crypto regulation

We begin our analysis with an assessment of the drivers of crypto regulation. We are interested in testing whether the presence of different pressure groups can explain the development of such regulation. We therefore regress our index of regulatory comprehensiveness on the measures that proxy for pressure from consumers and from funding actors, like VCs. Due to the count-like nature of the dependent variable, we test our hypothesis fitting a Poisson specification.[13]

The results are reported in Table 2. Column (I) reports the results of a Poisson regression of CRegIn on the one-month lag of the number of consumer complaints (per mn people) related to cryptocurrencies and its interaction term with the indicator variable identifying financial hubs; in Column (II) the explanatory variable is the one-month lag of per capita lobbying expenses. Column (III) shows the results of a regression in which both variables are included at the same time. The results show that both types of pressure groups were successful in their efforts to regulate the sector.

The development of the financial system could significantly impact how VC funding demands regulatory changes.[14] In line with the theories of economic regulation, we expect that the funding lobbying will be more active in those states where the financial sector is stronger. Therefore, we divide our sample in two groups depending on their aggregate finance and insurance GDP before 2010.

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13 We repeat this exercising fitting an OLS model in unreported robustness regressions and the results are qualitatively similar.

14 For example, in a way similarly to how the overall level of financial development and real outcomes interact (Rajan and Zingales, 1998; Guiso et al., 2004; Kerr and Nanda, 2011).

The relation between consumers' complaints and regulation is the same in all states, as displayed by the insignificant interaction term in Column (I). Lobbying, however, is associated with comparatively more regulation in those states where the financial sector constitutes a larger share of the overall economy. The effect of lobbying in financial hubs is four times larger relative to non-financial hubs (column II). This heterogeneous demand for regulation depending on the level of financial development of a state motivates us to look further on the effects on VC investment.

Table 2: Motivations for developing a comprehensive regulatory framework

	Dependent Variable: $\text{CRegIn}_{s,t}$		
Explanatory variables	(I)	(II)	(III)
Consumer complaints$_{s,t-1}$	0.226***		0.226***
	(0.03)		(0.03)
$\mathbb{1}$ [Fin hub state$_s$] $\times$ Consumer complaints$_{s,t-1}$	0.039		0.041
	(0.06)		(0.06)
Lobbying$_{s,t-1}$		0.029***	0.029***
		(0.00)	(0.00)
$\mathbb{1}$ [Fin hub state$_s$] $\times$ Lobbying$_{s,t-1}$		1.472***	2.089**
		(0.68)	(0.87)
Observations	6,510	6,510	6,510
Pseudo R^2	0.231	0.194	0.232

NOTE: Monthly data from 2010 to 2022. The sample includes all states except for Alaska and Mississippi, for which there is no information on VC crypto activity. The entries denote the coefficients of Poisson pseudo-maximum-likelihood regressions. The dependent variable $\text{CRegIn}_{s,t}$ is sum of items a law was in force for state s and month t. Consumer complaints$_{s,t-1}$ corresponds to the number of consumer complaints per mn people related to cryptocurrencies for state s and month $t-1$. Lobbying$_{s,t-1}$ corresponds to the dollar amount per capita spent on lobbying on issues related to cryptocurrencies by firms in state s and month $t-1$. Fin hub is an indicator variable that takes value one for states with aggregate sectoral GDP for the Finance and Insurance sector for the period 2010–2022 above the median of the distribution. Regressions include state fixed effects. Standard errors in parentheses are clustered by state: * $p < .10$; ** $p < .05$; and *** $p < .01$.

4.2 Regulation and private market deals

We next test if at the state level, more regulation of crypto applications is associated with more private market deals. To this end, we fit a state-month-year OLS specification with the following functional form:

$$\ln\left(y_{s,t}\right) = \beta \text{CRegIn}_{s,t} + \gamma \text{CRegIn}_{s,t} \times \mathbb{1}\left[\text{Fin Hub}_s\right] + \alpha_s + \theta_t + \varepsilon_{s,t}, \tag{1}$$

where the dependent variable $\ln(y_{s,t})$ is either the logarithm of capital raised or the logarithm of the number of deals in state s at month-year t, $\text{CRegIn}_{s,t}$ refers to the Crypto Regulation Index we introduced in Section 3.1, $\mathbb{1}\left[\text{Fin Hub}_s\right]$ is an indicator variable that takes a value of one for states that have an aggregate sectoral GDP for the finance and insurance sector above the median, and α_s and θ_t correspond to state- and time fixed effects, respectively.

The results, which are reported in Table 3 show that more crypto regulation is positively associated with both a larger amount of funds raised and a higher number of deals (Columns I and V). To understand which states drive this relation, we compare financial hubs with other states using an interaction term (Columns II and VI) and running regressions separately for the two sub-samples (Columns III, IV, VII and VIII). We find that regulation is positively and significantly correlated with VC funding only in financial hubs, as reported by the non-statistically significant results for non financial hubs in columns IV and VIII. The magnitude of the coefficients is economically significant. For example, a one-standard deviation increase in CRegIn is associated to an increase in the capital raised of about 30% (column III) in financial hubs. In Appendix A we explore a number of instruments for the index that account for possible confounding factors, and find that our results hold.

Table 3: Regulatory comprehensiveness and deal making activity

	ln(capital raised$_{s,t}$)				ln(number deals$_{s,t}$)			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
CRegIn$_{s,t}$	0.146**	-0.077	0.185**	0.075	0.076*	-0.063	0.095*	0.033
	(0.068)	(0.079)	(0.079)	(0.058)	(0.042)	(0.043)	(0.049)	(0.027)
$\mathbb{1}$ [Fin Hub$_s$] × CRegIn$_{s,t}$		0.331***				0.208***		
		(0.087)				(0.046)		
Observations	7644	7644	3900	3744	7644	7644	3900	3744
Sample	Pooled	Pooled	Fin. hub	Non Fin. hub	Pooled	Pooled	Fin. hub	Non Fin. hub
Adjusted R-squared	0.43	0.46	0.5	0.21	0.58	0.61	0.64	0.29

NOTE: Monthly data from 2010 to 2022. The sample in columns I–II and V–VI includes all states except for Alaska and Mississippi, for which there is no information on VC crypto activity. The sample in columns III and VII includes financial hub states only. The sample in columns IV and VIII includes non financial hub states only. Fin hub is an indicator variable that takes value one for states with aggregate sectoral GDP for the Finance and Insurance sector for the period 2000–2009 above the median of the distribution. The entries denote the coefficients of a panel-OLS regression. Regressions include state- and time fixed effects. Standard errors in parentheses are clustered by state: $*$ $p < .10$; ** $p < .05$; and *** $p < .01$.

5 Economic channel: more comprehensive regulation alleviates information asymmetry

In this section we investigate the channel through which more regulation is associated with more funding for firms, as found in Section 4.2. Specifically, we posit that additional regulation alleviates the asymmetric information problems that plague young and innovative firms, thus simplifying their access to private capital markets. Guided by the results in Section 4.2, we focus on an event increasing regulatory comprehensiveness in a financial hub state: the introduction of the BitLicense in New York. To explore the economic channel, we rely on granular deal-level data.[15]

[15] Another state that has passed substantial crypto regulation is Wyoming. This state, however, does not qualify as a financial hub. The data do not show any sustained increase in VC funding in Wyoming, consistent with our finding in Section 4.2. Furthermore, it is not clear that the regulatory push coincides with individuals and investors' sentiment (See The Economist Wyoming wants to become America's crypto capital.)

We focus on New York as a case study for two reasons: first, the BitLicense passed in 2015, when crypto deals had picked up and thus there is enough pre-event information. Additionally, the BitLicense is considered the most comprehensive license to operate in the U.S. Understanding its effect on different areas of the crypto ecosystem can provide indications for other states considering the introduction of similar licenses.

5.1 BitLicense institutional details

On June 24, 2015 the New York Department of Financial Service (NYDFS) issued Virtual Currency Regulation 23 NYCRR Part 200 under the New York Financial Services Law to provide regulatory clarity to business active in the cryptocurrency space.[16] The regulation, also known as *BitLicense*, introduces the requirement to obtain a specific business license to conduct cryptocurrency related activities in the state of New York. Its objective is to increase transparency, impacting both customers and investors.[17]

The obligation to have a BitLicense, which imposes disclosure and capital requirements on firms operating in the crypto sphere, applies to those engaging in virtual currency business activities either involving New York residents or taking place in the state of New York (see 23 NYCRR 200.2(q)). The regulated activities include receiving or transmitting virtual currency; storing, holding, or maintaining custody or control of virtual currency on behalf of others; buying and selling virtual currency as a business (not as an individual); performing exchange services as a business; or controlling, administering, or issuing a virtual currency. The requirements are comprehensive and require firms to disclose a substantial amount of information, such as detailed business plans, financial statements, and a description of each type of

[16] See Virtual Currency Businesses: Main Page - DFS.NY.gov for further details.
[17] See NY DFS Releases Proposed BitLicense Regulatory Framework For Virtual Currency Firms for further details.

transaction or service to be conducted.[18] The NYDFS granted its first BitLicense on September 22, 2015.[19]

Our focus with this exercise is whether a more comprehensive regulatory environment in the state of New York, through the introduction of the BitLicense, facilitated VC funding of firms most affected by information asymmetries operating in the sector. We do not establish the direct effect of being awarded a BitLicense for those firms that received it. As the BitLicense required greater transparency to engage in crypto-related activities, investment into traditionally more opaque firms–like start-ups and younger firms–could have increased.[20] The BitLicense could have an impact beyond its direct effect on crypto ventures. An example of crypto-adjacent start-ups impacted by the license would be those that develop software used by crypto platforms. Although software development itself does not require a BitLicense, funding for software development firms can be impacted by the introduction of the license, as the users of the software would be covered by the new requirements.

5.2 Empirical strategy

To disentangle the effect of additional regulation on information asymmetries, we run difference-in-differences specifications at the firm-quarter-year level on a window of two years around the introduction of the Bitlicense ie Q3 2013–Q3 2017.

5.2.1 Building a control group

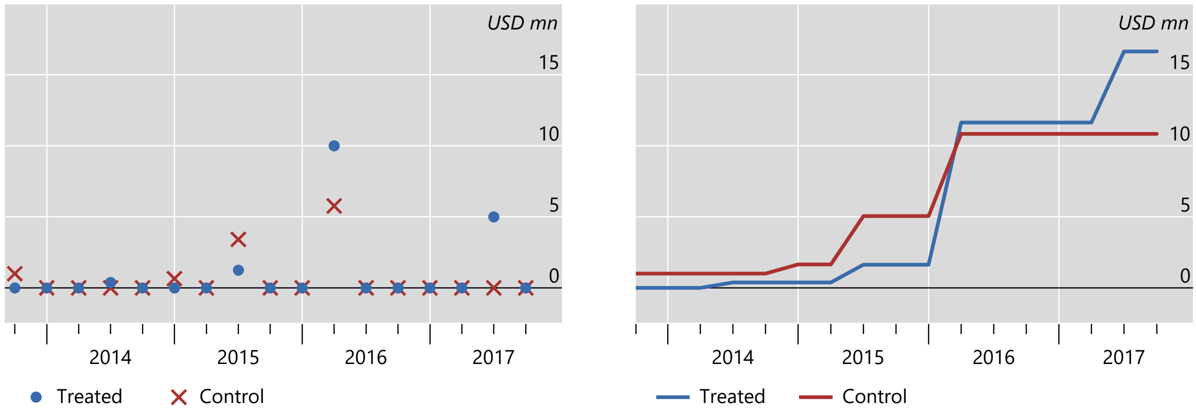
The treated firms are those headquartered in New York after the introduction of the BitLicense. To construct a control group as close as possible to the treatment group, we employ coarsened exact matching (CEM) (Blackwell et al., 2009). This procedure

[18] For details see NY Virtual Currency Business Activity License New Application Checklist.
[19] See NYDFS announces approval of the first BitLicense application form a virtual currency firm.
[20] See for example this WSJ interview with the Coinbase CEO.

assigns firms to the control group by matching those that are statistically similar to the treated firms in terms of observable characteristics.[21] Specifically, we match based on firm characteristics: age, sector of operations, type of deal, CEO gender and level of education. To control for state differences in regulatory attitudes, we also match based on the state CRegIn.

Figure 3: **Fundraising activity by a representative firm**

(a) Capital raised (b) Cumulative capital raised



Note: The left-hand (right-hand) panel shows the (cumulative) capital raised by a representative treated and control firm.
Source: PitchBook Data Inc; authors' calculations.

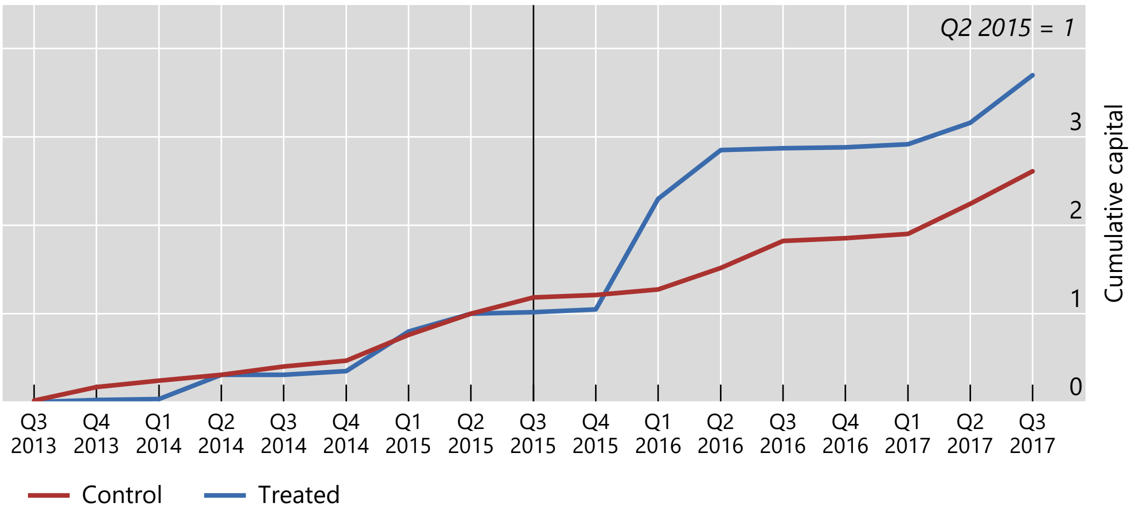
Figure 3 provides a visual representation of the fundraising activity of two matched firms, one in New York (treated, blue dots) and another one in a different state (control, red crosses). The capital raised by a firm through private market deals follows a jump process (panel (a)): between 2010 and 2018, firms raise money on average 2.3 times (with a standard deviation of 1.6), and the amounts vary in each of the capital rounds. Capital raised is zero in those periods when no deal is closed. Taking capital raised in a given deal, ie the deal size, as the dependent variable corresponds to estimating the effect on the average deal size. Since we are interested in estimating the effect of a more

[21] Coarsening of controls maximizes the balancedness in covariates and guarantees that most treated observations have a match (Iacus et al., 2012).

comprehensive regulatory environment on total capital raised, and not on the average deal size, we take cumulative capital as the dependent variable for our analysis (panel (b)).[22]

Figure 4 shows the average cumulative capital raised by treated and untreated firms, normalized to their value in the quarter right before treatment (ie the second quarter of 2015). Before the introduction of the BitLicense, firms in the treatment and the control group showed a similar evolution in their cumulative capital raised. However, two years after the regulatory environment became more comprehensive, firms based in New York raised, on average, 1.4 times the amount raised by the firms in the control group.

Figure 4: **Cumulative capital around the BitLicense**



NOTE: The figure shows the simple average of the cumulative capital raised by treated- and control firms. The black vertical line indicates $t0$ –ie 2015 Q3 –the quarter when the NY DFS BitLicense is introduced.
SOURCE: PitchBook Data Inc; authors' calculations.

5.2.2 Regression specification

We estimate Poisson Pseudo Maximum Likelihood regressions (Chen and Roth, 2024; Mullahy and Norton, 2022). Specifically, we fit the following specification at the firm i

[22] See Beraja et al. 2023.

quarter-year t level:

$$y_{i,t} = \exp\left(\beta \mathbb{1}\left[\text{Post}_t\right] \times \mathbb{1}\left[\text{NY}_i\right] \times \mathbb{1}\left[\text{IA}\right] + \ X'_{i,t}\gamma + \alpha_i + \theta_t + \varepsilon_{i,t}\right) \tag{2}$$

The dependent variable $y_{i,t}$ is the cumulative capital raised by firm i from the beginning of our observation window up to quarter-year t. The indicator variable $\mathbb{1}\left[\text{Post}_t\right]$ equals one after the introduction of the BitLicense. The dummy variable $\mathbb{1}\left[\text{NY}_s\right]$ varies at the state level and takes the value of one for firms headquartered in New York and zero otherwise.

The indicator variable $\mathbb{1}\left[\text{IA}\right]$ varies at the firm- or firm-time level and identifies firms for which information asymmetries are stronger. Depending on the specification, it signals whether the firm is less than two years old ($\mathbb{1}\left[\text{Young}_{i,t}\right]$), newly created in the year ($\mathbb{1}\left[\text{Start-up}_{i,t}\right]$), or has limited asset pledgeability ($\mathbb{1}\left[\text{Low collateral}_i\right]$).[23] The coefficient of interest β corresponds to the estimated change in cumulative capital raised after the introduction of the BitLicense for firms that are more affected by information asymmetries versus others. $X_{i,t}$ is a vector of the controls included in the matching. α_i and θ_t correspond to firm- and time fixed effects. Firm fixed effects control for firm-specific unobserved characteristics that our dataset might not include, like CEO productivity or market strategies. Time (quarter-year) fixed effects control for time-specific trends that are common to all firms, like overall trends in crypto-VC funding or the price of crypto currencies. We cluster standard errors at the state level.

Table 4: Regulatory stringency and information asymmetries

	Dependent Variable: Cumulative capital raised$_{i,t}$							
Explanatory Variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i]$	0.228***	0.582	0.180**	0.544	0.210***	0.901	−0.250	0.203
	(0.07)	(0.64)	(0.07)	(0.58)	(0.05)	(0.58)	(0.29)	(0.73)
$\mathbb{1}[\text{Young}_{i,t}]$			−0.537	−0.276				
			(0.35)	(0.35)				
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Young}_{i,t}]$			0.296	0.231				
			(0.25)	(0.26)				
$\mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Young}_{i,t}]$			−1.229***	−1.383***				
			(0.32)	(0.35)				
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Young}_{i,t}]$			0.542**	0.881***				
			(0.27)	(0.30)				
$\mathbb{1}[\text{Start-up}_{i,t}]$					−0.669**	−0.436		
					(0.30)	(0.32)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Start-up}_{i,t}]$					−0.063	−0.174		
					(0.40)	(0.38)		
$\mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Start-up}_{i,t}]$					−0.989***	−1.299***		
					(0.35)	(0.33)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Start-up}_{i,t}]$					1.740***	2.109***		
					(0.41)	(0.38)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Low-collateral}_i]$							−0.315	−0.375
							(0.34)	(0.44)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Low-collateral}_i]$							0.996***	1.249**
							(0.34)	(0.49)
Controls		✓		✓		✓		✓
Observations	2,584	2,584	2,584	2,584	2,584	2,584	2,584	2,584
Pseudo R^2	0.881	0.897	0.885	0.899	0.883	0.898	0.882	0.898

NOTE: Firm-level data for the 8 quarters before to the 8 quarters after the introduction of the New York DFS BitLicense ie Sep 2013 to Jun 2017. The table reports the coefficients of Poisson pseudo-maximum-likelihood regressions. The dependent variable *Cumulative capital raised*$_{i,t}$ is the cumulative capital raised by firm i up to period t. $Young_{i,t}$ is and indicator variable that takes value one when firm age is less than 2 years old. $Start-up_{i,t}$ is and indicator variable that takes value one in the year the firms is founded. $Low-collateral_i$ is and indicator variable that takes value one when primary business group is Software (Aboody and Lev, 2000; Trester, 1998). Regressions include firm- and time fixed effects. Controls are firm age, CEO- gender and education level, deal type, firm- status and number of deals, and $\text{CRegIn}_{s,t-1}$. Regressions are weighted by CEM weights. Standard errors in parentheses are clustered by state: * $p < .10$; ** $p < .05$; and *** $p < .01$.

5.3 Results

Table 4 reports the regressions results.[24] The positive and statistically significant coefficient from column I is consistent with the effect found for financial hubs in Section 4.2; a more comprehensive regulatory environment has a positive effect on capital raised by treated firms. In dollar terms, the effect corresponds to an increase in total capital raised of more than USD 1.1 millions, on average. The effect is somewhat larger, but comparable to the USD 700,000 found by Cornelli et al. 2024 in the context of the UK FCA regulatory sandbox.

Column III introduces the triple interaction term for young firms. Capital raised by young firms in the state of New York is significantly higher (almost three-quarters more) compared to older, more established firms. Our results remain robust after controlling for firm- and deal level characteristics in column IV.

Our results rely on the assumption that the treated and untreated firms followed a similar trend before the introduction of the BitLicense. We therefore estimate how cumulative capital raised by young firms in the state of New York changes with respect to older firms in each quarter. Figure 5 reports the results of this analysis, where each dot corresponds to the triple interaction term of an expanded variant of Equation 2, in which we replace the indicator variable $\mathbb{1}\left[\text{Post}_t\right]$ with an indicator variable for each quarter-year. The quarter before the BitLicense's introduction (ie Q2 2015) is the omitted category. Figure 5 shows that there is no discernible difference in the cumulative capital

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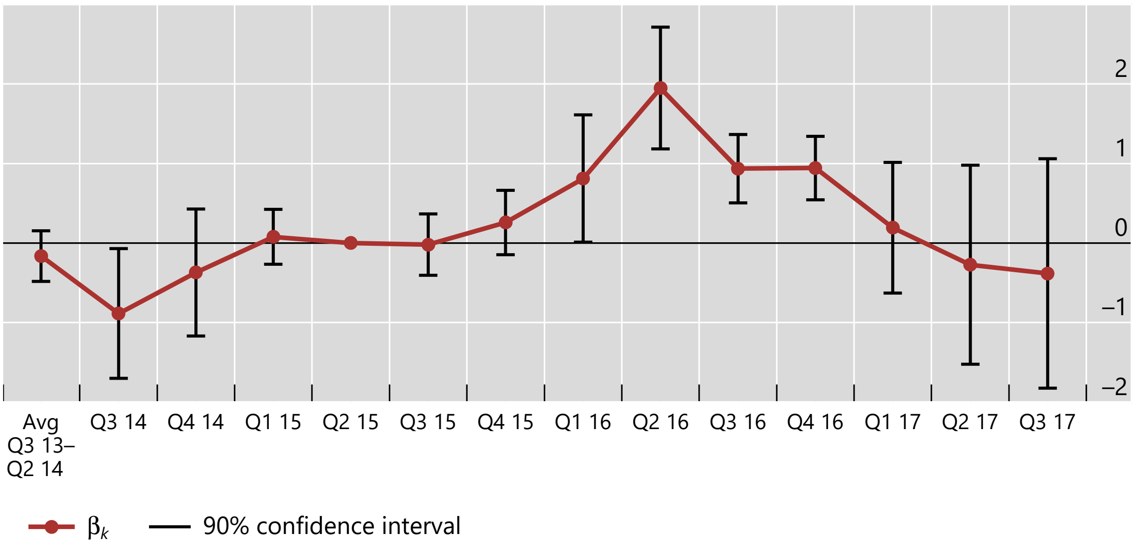
[23] Extensive literature indicates that information asymmetries are more pronounced for young firms (Morellec and Schürhoff, 2011), start-ups (Conti et al., 2013), and firms with less tangible assets that could be pledged as collateral as, for example, software firms (Chung et al., 2010; Goyal and Wang, 2013).

[24] Throughout the paper, we winsorize capital raised at the 2% level. We do so to avoid that a single outlier deal drives our results. One concern, however, could be that the bigger VC firms only engage in such big deals and hence our results would not be representative of their behaviour. In unreported regressions, we run Equation 2 without winsorizing the dependent variable and find that the results remain consistent.

raised by young and old firms in the periods before the introduction of the BitLicense in New York. However, capital raised by younger firms increases significantly more compared to older firms after the BitLicense came into effect. The effect persistently lasts for five quarters and levels out from the sixth quarter onward.[25]

Figure 5: **Coefficient plot: pre-trends**



NOTE: The figure shows coefficient estimates for the regression $y_{i,t} = \exp\left(\sum_{k=-8}^{K=8} \beta_k \mathbb{1}\left[\text{quarter}_t\right] \times \mathbb{1}\left[\text{NY}_i\right] \times \mathbb{1}\left[\text{IA}\right] + X'_{i,t}\gamma + \alpha_i + \theta_t + \varepsilon_{i,t}\right)$, where the coefficient β_k corresponds to the estimated change in cumulative capital raised k quarters before or after the introduction of the BitLicense for firms that are more affected by information asymmetries versus the others. Regressions are weighted with the respective CEM weights. We average coefficients for -8 to -5 quarters before the treatment date as not all of these are identified due to data limitations.
SOURCE: PitchBook Data Inc; authors' calculations.

For further evidence that our proposed mechanism drives the results, we zoom in on the youngest possible firms, newly founded start-ups. Columns V and VI of Table 4 report the results for start-up firms and show that the effects are stronger than for the young firms. Start-up firms in the state of New York raise significantly more capital than established firms. The effect is economically sizable and corresponds to 5.7x–8.2x more in total capital raised by treated start-up firms relative to the older firms based in the same state. In absolute terms, the overall effect for start-ups corresponds to an increase in

[25] Pre-trends for start-up firms also hold, albeit with more noise given that the sample size is smaller.

total capital raised of about 22% (column VI), a magnitude that corresponds to around USD 925,000 based on the average cumulative capital raised.[26] The start-up results suggest that a more comprehensive regulatory framework also encouraged the extensive margin, ie, the creation of new firms.[27] Our result is consistent with and somewhat larger than what Gonzalez-Uribe and Leatherbee 2018 find for the accelerator *Start-up Chile* (see their Table 6) and Howell 2017 finds in the context of the SBIR program (see Table 3). Overall, this finding also suggests that regulatory comprehensiveness does not discourage the entry of new players by raising barriers to entry.

Finally, columns VII and VIII focus on firms operating in the software industry, which is characterized by low collateral. The results show that, after the introduction of the BitLicense in New York, these firms raise significantly more capital. Overall, evidence from Table 4 provides empirical support for our proposed channel: more regulation alleviates information asymmetries and facilitates access to capital for those firms that are more constrained.

One concern is that the majority of VC funding happens in the states of California and New York (Howell, 2020). New York in particular has attracted several innovative fintech startups. Thus, VC funding for start-ups could increase in New York over time for factors different from regulation. We address these concerns with two robustness tests in Subsection 5.3.3. First, we run a falsification test considering deals in California, rather than in New York, as the treatment group (see Table 8). Second, we compare crypto firms to other fintech (non-crypto) firms within the state of New York (see Table 9). If the confounding factors drive our results, we would expect a positive and statistically significant coefficient for the triple interaction term in the test using California as the

[26] Calculated as the sum of the coefficients $\mathbb{1}\,[\text{Start-up}_i] + \mathbb{1}\,[\text{Post}_i] \times \mathbb{1}\,[\text{Start-up}_i] + \mathbb{1}\,[\text{NY}_i] \times \mathbb{1}\,[\text{Start-up}_i] + \mathbb{1}\,[\text{Post}_i] \times \mathbb{1}\,[\text{NY}_i] \times \mathbb{1}\,[\text{Start-up}_i]$. The p-value of the corresponding F-test is 0.003.

[27] We looked for evidence that existing young firms relocate to New York after the introduction of the BitLicense. The data on relocation, however, is very sparse. For example, data from SEC Form D (Chen and Ewens, 2024) shows that only 2.5% of all reporting U.S. firms relocate during our sample period.

treatment group and non statistically significant results in the test comparing firms within the state of New York. This is not what we find: overall, the results from these tests confirm our proposed explanation.

Alternative channels Besides a reduction in information asymmetries, there may be other forces at play, such as a reduction in policy uncertainty. First, the entry of traditional financial institutions –such as banks –in the cryptocurrency market could have encouraged VC investment. However, such entry occurred long after the introduction of the BitLicense as showed in Figure B1 and is therefore unlikely to be the channel behind our findings. Second, regulation creates compliance costs that could advantage incumbents. Thus, more raised capital could reflect less competition for incumbents or investment options rather than better information. The result for start-ups in Table 4 column VI, which can be interpreted in terms of extensive margins, suggests that start-ups significantly raise more money relative to more established firms. Therefore, barriers to entry do not seem to be the driving force behind our findings. Third, regulation might facilitate coordination by establishing common standards and the resulting network effects could lead to post-regulation geographic concentration. In this case, increases in funding would be due to the network effect and not to a reduction of information asymmetries. Unfortunately, given the early stage of the industry, there are no data to test this channel. Fourth, increased funding may come from lower required returns rather than higher expected cash flow. As the terms of the VC deals are not public, we cannot test the role and contribution of systemic risk reduction in our findings. Despite these caveats, our findings are consistent with a reduction in information asymmetries and suggest that it plays an important role behind VC funding.

5.3.1 Ex-post survival

As an additional test, we check if by October 2023 the firms that raised money after the introduction of the BitLicense continued to operate or had gone bankrupt. Column I in Table 5 shows that among young firms, firms that are operating by October 2023 raised 3 times more capital that the ones that end up going bankrupt, an economically sizable effect. Column II estimates the regression on the subsample of firms that eventually went bankrupt. The results show that young firms belonging to this group raised less capital. Column III estimates the same regression on the subsample of firms that did not go bankrupt. Among those firms, following the introduction of the BitLicense, young firms raise more capital than old firms. Column IV shows that results are consistent if we consider all firms together. Overall, evidence from Table 5 provides empirical support to the role of regulatory comprehensiveness in alleviating asymmetric information and enabling more capital to flow to firms that (ex-post) survive.

5.3.2 Investors' characteristics and information asymmetries

Not all investors are equally affected by information asymmetries. A closer relationship or shorter geographical distance between investors and target firms helps alleviate information frictions (Grinblatt and Keloharju, 2001; Degryse and Ongena, 2005).[28] Thus, in our setting, information asymmetries should be stronger for investors that are based outside of the United States (ie foreign investors), since they have an information disadvantage when investing into U.S. firms; for investors that are not specialised in crypto, as they have less industry knowledge; and small investment firms (ie investors with few investment professionals), since the cost of acquiring information for these firms is larger given the smaller headcount. We define a non-specialist investor as

[28] Coval and Moskowitz 1999 document that investors tend to invest a larger share of their portfolio in stocks of firms that are geographically close. Ivković and Weisbenner 2005 find that investors earn abnormal returns on stocks of firms that are physically closer.

Table 5: Regulatory stringency and ex-post survival

	Dependent Variable: Cumulative capital raised$_{i,t}$			
Explanatory Variables	(I)	(II)	(III)	(IV)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i]$	-0.152	4.404	0.685	1.324**
	(0.67)	(3.43)	(0.57)	(0.60)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Survival}_i]$	-0.542			0.421**
	(0.46)			(0.20)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Survival}_i]$	1.162***			-0.692***
	(0.44)			(0.15)
$\mathbb{1}[\text{Young}_{i,t}]$		-0.546**	0.044	-1.551**
		(0.28)	(0.43)	(0.72)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Young}_{i,t}]$		0.686***	0.066	1.189**
		(0.26)	(0.27)	(0.57)
$\mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Young}_{i,t}]$		0.566*	-2.178***	1.535**
		(0.34)	(0.41)	(0.72)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Young}_{i,t}]$		-0.333*	1.241***	-0.973*
		(0.19)	(0.31)	(0.56)
$\mathbb{1}[\text{Young}_{i,t}] \times \mathbb{1}[\text{Survival}_i]$				1.550
				(0.95)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Young}_{i,t}] \times \mathbb{1}[\text{Survival}_i]$				-1.048
				(0.70)
$\mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Young}_{i,t}] \times \mathbb{1}[\text{Survival}_i]$				-3.662***
				(0.93)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Young}_{i,t}] \times \mathbb{1}[\text{Survival}_i]$				2.200***
				(0.76)
Sample of firms	Young	Eventually bankrupt	No bankruptcy	All
Observations	1,370	697	1,887	2,584
Pseudo R^2	0.792	0.792	0.914	0.901

NOTE: Firm-level data for the 8 quarters before to the 8 quarters around the introduction of the New York DFS BitLicense ie Sep 2013 to Sep 2017. The table reports the coefficients of Poisson pseudo-maximum-likelihood regressions. The dependent variable *Cumulative capital raised*$_{i,t}$ is the cumulative capital raised by firm i up to period t. $Young_{i,t}$ is and indicator variable that takes value one when firm age is less than 2 years. $Survival_i$ is and indicator variable that takes value 0 if by October 2023 firm i went bankrupt, 1 if it is still in business. Regressions include firm- and time fixed effects. Controls are firm age, CEO- gender and education level, deal type, firm- status and number of deals, and $CRegIn_{s,t-1}$. Regressions are weighted by CEM weights. Standard errors in parentheses are clustered by state: * $p < .10$; ** $p < .05$; and *** $p < .01$.

those for which "cryptocurrency" does not appear among the preferred investment themes according to the respective stated preferences and past investment history. To investigate if the investor angle confirms our finding that a more comprehensive regulatory framework leads to a reduction in information asymmetries, in what follows, we perform analyses at the investor-firm-time level. Specifically, we estimate the following equation:

$$y_{j,i,t} = \exp\left(\beta \mathbb{1}\left[\text{Post}_t\right] \times \mathbb{1}\left[\text{NY}_i\right] \times \mathbb{1}\left[\text{Investor}_j\right] + \alpha_{j,i} + \theta_{k,t} + \varepsilon_{j,i,t}\right) \tag{3}$$

The dependent variable $y_{j,i,t}$ is the cumulative capital invested by investor j, in firm i from the beginning of our observation window up to quarter-year t. For those deals that are syndicated, we divide the total amount among the investors equally. Our results are robust to alternative methodologies for splitting the investment amount among investors (see 5.3.3). The indicator variable $\mathbb{1}\left[\text{Investor}_j\right]$ corresponds to investor-level characteristics proxying for the degree of information asymmetry to which they are exposed (ie foreign, non-specialised or small). We include investor $\times$ firm fixed effects (ie $\alpha_{j,i}$) to account for unobservable heterogeneity within each firm-investor combination (Jiménez et al., 2014), and industry $\times$ time fixed effects (ie $\theta_{k,t}$) to account for unobservable time-varying characteristics at the industry level, like aggregate demand factors.

Table 6 reports our findings. The positive and statistically significant coefficient in column I suggests that a more comprehensive regulatory framework leads to more capital invested. The triple interaction term (ie $\mathbb{1}\left[\text{Post}_t\right] \times \mathbb{1}\left[\text{NY}_i\right] \times \mathbb{1}\left[\text{Foreign investor}_j\right]$) in column II shows that after the introduction of the BitLicense foreign investors invest nearly twice more capital in New York based firms. Consistently, results from column III suggest that investors that do not have the crypto sector as a typical investment target increase their investment of about 40%. Similarly, the positive and statistically significant coefficient $\mathbb{1}\left[\text{Post}_t\right] \times \mathbb{1}\left[\text{NY}_i\right] \times \mathbb{1}\left[\text{Small investment firm}_j\right]$ in column IV confirms our finding for small investment firms. Overall, our findings show that investors that are typically more affected by information asymmetry like foreign, non-specialist investors, and small investment firms comparatively invest more capital under a more comprehensive regulatory framework.

Table 6: Investors' characteristics and informational asymmetries

	Dependent Variable: Cumulative capital invested$_{j,i,t}$			
Explanatory variables	(I)	(II)	(III)	(IV)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i]$	0.515***	0.383***	0.288**	0.331*
	(0.14)	(0.14)	(0.13)	(0.17)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}\left[\text{Foreign investor}_j\right]$		0.462*		
		(0.27)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}\left[\text{Foreign investor}_j\right]$		0.550**		
		(0.27)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}\left[\text{Non-specialist investor}_j\right]$			−0.078	
			(0.13)	
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}\left[\text{Non-specialist investor}_j\right]$			0.327**	
			(0.13)	
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Small investment firm}_j]$				−0.328***
				(0.09)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Small investment firm}_j]$				0.543***
				(0.13)
Observations	21,968	21,935	21,935	21,968
Pseudo R^2	0.646	0.648	0.646	0.647

NOTE: Investor-firm level data for the 8 quarters before to the 8 quarters after the introduction of the New York DFS BitLicense ie Sep 2013 to Jun 2017. The table reports the coefficients of Poisson pseudo-maximum-likelihood regressions. The dependent variable *Cumulative capital invested*$_{j,i,t}$ is the cumulative invested raised by each investor j in firm i up to quarter t, based on a pro-rata split of the overall deal amount. *Foreign investor*$_j$ is and indicator variable that takes value one if the investor is not headquartered in the United States. *Non-specialist investor*$_j$ is an indicator variable that takes value one if cryptocurrency is not a sector that the investor typically targets. *Small investment firm*$_j$ is and indicator variable that takes value one when the investor has less than five investment professionals. Regressions include investor × firm- and industry × time fixed effects. Standard errors in parentheses are clustered by state: * $p < .10$; ** $p < .05$; and *** $p < .01$.

5.3.3 Robustness tests

In this section we discuss a number of robustness checks. Certain industries within the crypto sector might have become more attractive to investors over time. To control for any such evolution we estimate Equation 2 replacing time-fixed effects with industry × time fixed effects. industry × time capture any differences by industry over time. Results from Table 7 are very similar to the baseline in Table 4, confirming that they are not driven by unobservable time-varying industry characteristic.

Table 7: Controlling for time-varying industry characteristics

	Dependent Variable: Cumulative capital raised$_{i,t}$			
Explanatory Variables	(I)	(II)	(III)	(IV)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i]$	0.469	0.357	0.879**	−0.432
	(0.52)	(0.47)	(0.44)	(0.73)
$\mathbb{1}[\text{Young}_{i,t}]$		−0.295		
		(0.33)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Young}_{i,t}]$		0.255		
		(0.27)		
$\mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Young}_{i,t}]$		−1.617***		
		(0.47)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Young}_{i,t}]$		1.065**		
		(0.46)		
$\mathbb{1}[\text{Start-up}_{i,t}]$			−0.440	
			(0.28)	
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Start-up}_{i,t}]$			−0.144	
			(0.37)	
$\mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Start-up}_{i,t}]$			−1.341***	
			(0.40)	
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Start-up}_{i,t}]$			2.110***	
			(0.57)	
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Low-collateral}_i]$				0.387
				(0.25)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Low-collateral}_i]$				1.466**
				(0.67)
Observations	2,455	2,455	2,455	2,455
Pseudo R^2	0.897	0.899	0.898	0.899

NOTE: Firm-level data for the 8 quarters before to the 8 quarters around the introduction of the New York DFS BitLicense ie Sep 2013 to Sep 2017. The table reports the coefficients of Poisson pseudo-maximum-likelihood regressions. The dependent variable *Cumulative capital raised*$_{i,t}$ is the cumulative capital raised by firm i up to period t. $Young_{i,t}$ is and indicator variable that takes value one when firm age is less than 2 years. $Low-collateral_i$ is and indicator variable that takes value one when primary business group is Software (Aboody and Lev, 2000; Trester, 1998). Regressions include firm- and industry $\times$ time fixed effects to control for time-varying unobservable characteristics at the industry level. Controls are firm age, CEO-gender and education level, deal type, firm- status and number of deals, and $CRegIn_{s,t-1}$. Regressions are weighted by CEM weights. Standard errors in parentheses are clustered by state: * $p < .10$; ** $p < .05$; and *** $p < .01$.

We also run a falsification test where the fictitious treatment group corresponds to firms based in California, instead of firms based in New York.[29] Notably, none of

[29] We select California as another VC Hub following Howell 2020. Results for Massachusetts, a smaller VC hub considered in Howell 2020, are similar to the California falsification test.

the coefficients of interest in Table 8 –ie the triple-interaction terms –are statistically significant.

We also re-estimate Equation 2 using a different definition for the control group. Specifically, instead of considering crypto firms based in states other than New York, we use firms within the state of New York but active in the fintech sector (excluding the crypto industry). Fintech firms constitute a correct comparison, as argued in Babina et al. (2022), as some of the technology they employ is similar to that of crypto-firms, but are covered by very different regulation. Furthermore, and particularly relevant for our setting, fintech firms not active in the crypto industry are not subject to the BitLicense. The fintech comparison allows us to rule out that certain state-specific unobservable characteristics drive our results in the main analysis. By focusing on firms in New York, we ensure that both treatment and control firms are exposed to the same generic state shocks. Table 9 reports the results. Overall, the results are consistent with the evidence from Table 4 and Table 5: it is unlikely that our results are driven by unobservable characteristics at the state level.

Furthermore, as VC is a particularly information-sensitive industry (Gompers, 1995; Howell, 2020), we verify that our findings persist when removing the few transactions belonging to other types of private deals (as described in Section 3). Results from Table 10 confirm our previous findings. Furthermore, coefficients from columns III and IV are somewhat larger in absolute value compared to the ones from Table 4 columns VI and VIII, respectively. Overall, our findings are consistent with the notion that a more comprehensive regulatory environment eases information asymmetries between firms and investors.

Table 8: Falsification test using California

	Dependent Variable: Cumulative capital raised$_{i,t}$					
Explanatory Variables	(I)	(II)	(III)	(IV)	(V)	(VI)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{CA}_i]$	0.208	0.340**	0.227	0.130	−0.102	0.453**
	(0.17)	(0.16)	(0.15)	(0.44)	(0.14)	(0.20)
$\mathbb{1}[\text{Young}_{i,t}]$		−0.695*			−0.570**	−0.585
		(0.38)			(0.29)	(0.48)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Young}_{i,t}]$		0.594***			0.687***	0.516**
		(0.22)			(0.25)	(0.21)
$\mathbb{1}[\text{CA}_i] \times \mathbb{1}[\text{Young}_{i,t}]$		−0.223			0.542*	−0.457
		(0.44)			(0.32)	(0.54)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{CA}_i] \times \mathbb{1}[\text{Young}_{i,t}]$		0.162			−0.232	0.358
		(0.23)			(0.18)	(0.22)
$\mathbb{1}[\text{Start-up}_{i,t}]$			−0.604**			
			(0.27)			
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Start-up}_{i,t}]$			0.619			
			(0.40)			
$\mathbb{1}[\text{CA}_i] \times \mathbb{1}[\text{Start-up}_{i,t}]$			−0.523			
			(0.34)			
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{CA}_i] \times \mathbb{1}[\text{Start-up}_{i,t}]$			−0.645			
			(0.39)			
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Low-collateral}_i]$				0.137		
				(0.47)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{CA}_i] \times \mathbb{1}[\text{Low-collateral}_i]$				0.087		
				(0.47)		
Sample of firms	All	All	All	All	Eventually bankrupt	No bankruptcy
Observations	2,839	2,839	2,839	2,839	714	2,125
Pseudo R^2	0.894	0.896	0.895	0.894	0.763	0.909

NOTE: Firm-level data for the 8 quarters before to the 8 quarters after the introduction of the New York DFS BitLicense ie Sep 2013 to Jun 2017. The table reports the coefficients of Poisson pseudo-maximum-likelihood regressions for a falsification test where the treated companies are located in California (instead of New York). The dependent variable *Cumulative capital raised*$_{i,t}$ is the cumulative capital raised by firm i up to period t. $Young_{i,t}$ is and indicator variable that takes value one when firm age is less than 2 years old. $Start-up_{i,t}$ is and indicator variable that takes value one in the year the firms is founded. $Low-collateral_i$ is and indicator variable that takes value one when primary business group is Software (Aboody and Lev, 2000; Trester, 1998). Regressions include firm- and time fixed effects. Controls are firm age, CEO- gender and education level, deal type, firm- status and number of deals, and $\text{CRegIn}_{s,t-1}$. Regressions are weighted by CEM weights. Standard errors in parentheses are clustered by state: * $p < .10$; ** $p < .05$; and *** $p < .01$.

Table 9: Using New York fintech firms as control group

	Dependent Variable: Cumulative capital raised$_{i,t}$						
Explanatory Variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Treated}_i]$	0.424***	0.512***	0.438***	0.446***	−1.627***	0.037**	0.531***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.49)	(0.02)	(0.00)
$\mathbb{1}[\text{Young}_{i,t}]$		−1.397***				0.739***	−1.400***
		(0.00)				(0.05)	(0.00)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Young}_{i,t}]$		1.555***				0.942***	1.433***
		(0.00)				(0.05)	(0.01)
$\mathbb{1}[\text{Treated}_i] \times \mathbb{1}[\text{Young}_{i,t}]$		−1.218***				1.076***	−1.422***
		(0.05)				(0.28)	(0.00)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Treated}_i] \times \mathbb{1}[\text{Young}_{i,t}]$		0.088***				−2.072**	0.268***
		(0.00)				(0.88)	(0.00)
$\mathbb{1}[\text{Start-up}_{i,t}]$			−1.400***				
			(0.00)				
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Start-up}_{i,t}]$			1.929***				
			(0.01)				
$\mathbb{1}[\text{Treated}_i] \times \mathbb{1}[\text{Start-up}_{i,t}]$			−0.661***				
			(0.01)				
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Treated}_i] \times \mathbb{1}[\text{Start-up}_{i,t}]$			0.889***				
			(0.01)				
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Low-collateral}_i]$				1.171***			
				(0.00)			
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Treated}_i] \times \mathbb{1}[\text{Low-collateral}_i]$				0.709***			
				(0.00)			
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Survival}_i]$					−0.125***		
					(0.01)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Treated}_i] \times \mathbb{1}[\text{Survival}_i]$					5.883***		
					(0.47)		
Sample of firms	All	All	All	All	Young	Eventually bankrupt	No bankruptcy
Observations	2,462	2,462	2,462	2,462	1,368	320	2,085
Pseudo R^2	0.894	0.905	0.899	0.901	0.841	0.870	0.909

NOTE: Firm-level data for the 8 quarters before to the 8 quarters after the introduction of the New York DFS BitLicense ie Sep 2013 to Jun 2017. The table reports the coefficients of Poisson pseudo-maximum-likelihood regressions. The treatment group corresponds to firms based in the state of New York and active in the crypto space. The contrl group corresponds to firms based in the state of New York and active in the fintech space (ie excluding crypto). The dependent variable *Cumulative capital raised*$_{i,t}$ is the cumulative capital raised by firm i up to period t. $Young_{i,t}$ is and indicator variable that takes value one when firm age is less than 2 years old. $Start-up_{i,t}$ is and indicator variable that takes value one in the year the firms is founded. $Low-collateral_i$ is and indicator variable that takes value one when primary business group is Software (Aboody and Lev, 2000; Trester, 1998). Regressions include firm- and time fixed effects. Controls are firm age, CEO- gender and education level, deal type, firm- status and number of deals, and CRegIn$_{s,t-1}$. Regressions are weighted by CEM weights. Standard errors in parentheses are clustered by city: * $p < .10$; ** $p < .05$; and *** $p < .01$.

Table 10: Regulatory stringency and information asymmetries for VC deals

	Dependent Variable: Cumulative capital raised$_{i,t}$			
Explanatory Variables	(I)	(II)	(III)	(IV)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i]$	0.591	0.542	0.909	0.155
	(0.63)	(0.57)	(0.57)	(0.75)
$\mathbb{1}[\text{Young}_{i,t}]$		−0.291		
		(0.36)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Young}_{i,t}]$		0.240		
		(0.27)		
$\mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Young}_{i,t}]$		-1.369***		
		(0.35)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Young}_{i,t}]$		0.872***		
		(0.31)		
$\mathbb{1}[\text{Start-up}_{i,t}]$			-0.429	
			(0.32)	
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Start-up}_{i,t}]$			-0.182	
			(0.38)	
$\mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Start-up}_{i,t}]$			-1.303***	
			(0.33)	
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Start-up}_{i,t}]$			2.111***	
			(0.38)	
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Low-collateral}_i]$				-0.432
				(0.48)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Low-collateral}_i]$				1.305**
				(0.53)
Observations	2,571	2,571	2,571	2,571
Pseudo R^2	0.897	0.900	0.899	0.899

NOTE: Firm-level data for the 8 quarters before to the 8 quarters around the introduction of the New York DFS BitLicense ie Sep 2013 to Sep 2017. The sample includes only firms financed by venture capital. The table reports the coefficients of Poisson pseudo-maximum-likelihood regressions. The dependent variable *Cumulative capital raised*$_{i,t}$ is the cumulative capital raised by firm i up to period t. $Young_{i,t}$ is and indicator variable that takes value one when firm age is less than 2 years. $Low - collateral_i$ is and indicator variable that takes value one when primary business group is Software (Aboody and Lev, 2000; Trester, 1998). Regressions include firm- and time fixed effects. Controls are firm age, CEO- gender and education level, deal type, firm- status and number of deals, and $CRegIn_{s,t-1}$. Regressions are weighted by CEM weights. Standard errors in parentheses are clustered by state: * $p < .10$; ** $p < .05$; and *** $p < .01$.

Finally, we corroborate the evidence from the investor-firm analysis using different definitions of the dependent variable. In Table 11, the dependent variable is computed by splitting the overall deal amount among all the investors participating to the deal proportionally to the number of investment professionals of each investor. In Table 12 the dependent variable is an indicator variable that takes value one if a given investor

j invests in firm i in quarter t and zero elsewhere. Overall, the evidence from Table 11 and Table 12 confirm the results from Table 6 suggesting that more comprehensive regulation leads to consequently more fund raising potentially through lower information asymmetries.

Table 11: Investors' characteristics and informational asymmetries: cumulative capital

	Dependent Variable: Cumulative capital invested$_{j,i,t}$			
Explanatory variables	(I)	(II)	(III)	(IV)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i]$	0.425***	0.252	0.156	0.308**
	(0.15)	(0.16)	(0.15)	(0.15)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Foreign investor}_j]$		0.282		
		(0.30)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Foreign investor}_j]$		0.576*		
		(0.33)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Non-specialist investor}_j]$			0.104	
			(0.12)	
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Non-specialist investor}_j]$			0.404***	
			(0.13)	
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Small investment firm}_j]$				−0.393***
				(0.15)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Small investment firm}_j]$				1.095***
				(0.21)
Observations	16,499	16,499	16,499	16,499
Pseudo R^2	0.767	0.768	0.767	0.768

NOTE: Investor-firm level data for the 8 quarters before to the 8 quarters after the introduction of the New York DFS BitLicense ie Sep 2013 to Jun 2017. The table reports the coefficients of Poisson pseudo-maximum-likelihood regressions. The dependent variable *Cumulative capital invested*$_{j,i,t}$ is the cumulative capital invested by each investor j in firm i up to quarter t, based on a split of the overall deal amount with weights proportional to the number investment professionals of each investor. *Foreign investor*$_j$ is an indicator variable that takes value one if the investor is not headquartered in the United States. *Non-specialist investor*$_j$ is and indicator variable that takes value one if cryptocurrency is not a sector that the investor typically targets. *Small investment firm*$_j$ is and indicator variable that takes value one when the investor has less than five investment professionals. Regressions include investor × firm- and industry × time fixed effects. Standard errors in parentheses are clustered by state: * $p < .10$; ** $p < .05$; and *** $p < .01$.

Table 12: Investors' characteristics and informational asymmetries: any capital raised

	Dependent Variable: Dummy capital raised$_{j,i,t}$			
Explanatory variables	(I)	(II)	(III)	(IV)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i]$	0.019***	0.010	−0.013*	0.008
	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Foreign investor}_j]$		0.029**		
		(0.01)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Foreign investor}_j]$		0.036***		
		(0.01)		
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Non-specialist investor}_j]$			−0.031***	
			(0.01)	
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Non-specialist investor}_j]$			0.047***	
			(0.01)	
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{Small investment firm}_j]$				−0.022***
				(0.00)
$\mathbb{1}[\text{Post}_t] \times \mathbb{1}[\text{NY}_i] \times \mathbb{1}[\text{Small investment firm}_j]$				0.026***
				(0.00)
Observations	22,627	22,576	22,576	22,627
R^2	0.045	0.047	0.046	0.046

NOTE: Investor-firm level data for the 8 quarters before to the 8 quarters after the introduction of the New York DFS BitLicense ie Sep 2013 to Jun 2017. The table reports the coefficients of panel OLS regressions. The dependent variable *Dummy capital raised*$_{j,i,t}$ is an indicator variable that takes value one if investor j invests in firm i in quarter t, and zero elsewhere. *Foreign investor*$_j$ is an indicator variable that takes value one if the investor is not headquartered in the United States. *Non-specialist investor*$_j$ is and indicator variable that takes value one if cryptocurrency is not a sector that the investor typically targets. *Small investment firm*$_j$ is and indicator variable that takes value one when the investor has less than five investment professionals. Regressions include investor × firm- and industry × time fixed effects. Standard errors in parentheses are clustered by state: * $p < .10$; ** $p < .05$; and *** $p < .01$.

6 Conclusions

In this paper, we use the cryptocurrency industry as a testing ground and study the drivers and the effects of the introduction of a new regulatory framework. We make four main contributions to the literature.

First, we develop an index of regulatory comprehensiveness for the crypto industry in the United States at the state-month level, based on a detailed review of legislation and official publications by regulatory authorities. We make the index available for future research, thereby contributing to the understanding of how crypto is regulated in the United States.

Second, we provide evidence consistent with crypto-regulation being the result of pressure from two distinct groups: consumers through complaints, and funding actors through lobbying. We also show that lobbying efforts were higher in financial hubs. These results are aligned with theories of economic regulation.

Third, we document a positive association between the amount of capital raised and the level of regulatory comprehensiveness across states as measured by our index. The result is entirely driven by financial hubs and suggest that VCs were successful in lobbying for rules that favoured investment in the industry.

Finally, we provide evidence –using the introduction of the BitLicense in New York as a regulatory shock– that is consistent with the reduction of information asymmetries as the mechanism driving the additional capital raised. We show that young firms, including start-ups, and firms in industries characterised by low collateral raised significantly more capital in New York after the introduction of the BitLicense than their counterparts. We also verify that investors facing higher information asymmetries before the BitLicense (foreign, not specialized in crypto, and smaller), allocate more money to these crypto ventures after the regulatory framework becomes more comprehensive.

Our results reveal the complex nature of regulatory interventions. Different groups with potentially diverging priorities (consumers and funding capital) have both been successful in pressuring public authorities to regulate the industry. This is not consistent with regulators being fully captured by the industry when regulating a nascent industry. In our case, we find that information asymmetries between venture capitalists and entrepreneurs decreased following the introduction of crypto regulation. Our results apply more widely to any nascent technology or sector beyond crypto, such as for example artificial intelligence.

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A Instrumenting crypto regulation

Our specification studying the association between crypto regulation and VC funding could suffer from endogeneity, biasing our coefficients upwards or downwards: on the one hand, state legislators may pass crypto related laws because they expect more VC investment into crypto-related ventures. On the other hand, they may pass laws aimed at curbing VC investment if they worry about VC encouraging an uncontrolled development of the industry. Additionally, there might be factors that change at the state-time level that are not captured by our fixed effects.

We address this issue by leveraging the geographic variation in the index. More similar states may have closer attitudes towards crypto regulation. The literature normally recognizes as more *similar* states those geographically closer (Acemoglu et al., 2019; Barth et al., 2013). In our case, as argued in Section 1, the crypto sector does not rely on geographical proximity to producers nor consumers to operate, which makes spatial correlation in regulatory requirements (changes in one state impacting its geographic neighbours) unlikely. Therefore we consider similar states based on the ranking of total VC funding over the period 2000–2009.[30]

We consider two alternative construction of the jack-knife averaged instrument: first, the lagged average of all the other states in our sample. The idea behind this instrument is that there is an underlying nationwide level of crypto regulatory comprehensiveness that is not correlated with state-level unobserved factors.

Additionally, we instrument the index with the one period lag of the average of the index in similar states. The logic behind this instrument is that more similar states have a shared level of regulatory comprehensiveness that is independent of crypto VC funding

30 A potential concern could be that the level of VC funding before the crypto sector took off is correlated with the level of regulatory comprehensiveness that states enact ex-post. However, the correlation between ex-ante VC funding and crypto regulatory comprehensiveness is very low.

in one particular state. Therefore, changes in peers' regulations only impact crypto VC funding in a state through the impact they have on the CRegIn of that specific state. We verify that our definition of financial hub does not alter the results by comparing those states in the top and bottom tercile instead of above/below the median.

Denote by $\mathcal{S}_{s,p}$ the set of states, excluding state s, that contains the $p \in \{10, 15\}$ closest states above and below state s in terms of the total VC capital raised over the period 2000–2009. Therefore, our instrument is $\overline{\text{CRegIn}_{\mathcal{S}_{s,p},t-1}}$.

The first stage regressions are:

$$\begin{aligned} \text{CRegIn}_{s,t} =& \psi\, \overline{\text{CRegIn}_{\mathcal{S}_{s,p},t-1}} + \eta\, \overline{\text{CRegIn}_{\mathcal{S}_{s,p},t-1}} \times \mathbb{1}\left[\text{Fin Hub}_s\right] \\ & + \omega_s + \tau_t + \upsilon_{s,t} \end{aligned} \tag{4}$$

$$\begin{aligned} \text{CRegIn}_{s,t} \times \mathbb{1}\left[\text{Fin Hub}_s\right] =& \zeta\, \overline{\text{CRegIn}_{\mathcal{S}_{s,p},t-1}} + \lambda\, \overline{\text{CRegIn}_{\mathcal{S}_{s,p},t-1}} \times \mathbb{1}\left[\text{Fin Hub}_s\right] \\ & + \kappa_s + \iota_t + u_{s,t} \end{aligned} \tag{5}$$

where ω_s, κ_s are state fixed effects and τ_t, ι_t are month-year fixed effects.

Finally, we use a different instrument for the regulatory comprehensiveness of the cryptocurrency ecosystem at the state level.[31] Specifically, we exploit the fact that the U.S. Department of Justice offers states funding opportunities to train officials and develop technical expertise, conduct research or collect national statistics, thereby improving the legal system of each state.[32] We instrument CRegIn with the one period lag of the total amount of grants awarded by the U.S. Department of Justice, Office of Justice Programs (DOJ-OJP) to each state. We posit that DOJ funding contributes to the development of higher quality regulation, which is likely correlated with better regulation of the crypto sector, but uncorrelated with the amount of capital raised in

[31] We are grateful to a number of seminar participants for helpful suggestions on potential alternative instruments.

[32] For further information see U.S. Department of Justice –Grants and U.S. Department of Justice, Office of Justice Programs –Grants/Funding.

each state. The exclusion restriction relies on capital raised by crypto firms being only influenced by the state regulatory quality through the state-specific cryptocurrency regulation. Under this identifying assumption, the coefficients can be interpreted causally.

Table A1: Regulatory comprehensiveness and deal-making activity: IV regressions

	(1) Capital	(2) Deals	(3) Capital	(4) Deals	(5) Capital	(6) Deals	(7) Capital	(8) Deals
$\text{CRegIn}_{s,t}$	-0.253*	-0.182**	-1.102	-0.865	-0.816	-0.641*	0.432	-0.065
	(0.140)	(0.086)	(0.818)	(0.555)	(0.519)	(0.329)	(1.268)	(0.498)
$\mathbb{1}\,[\text{Fin Hub}_s] \times \text{CRegIn}_{s,t}$	0.594***	0.385***	0.660**	0.425**	0.786***	0.445**	0.602**	0.198***
	(0.150)	(0.091)	(0.268)	(0.197)	(0.241)	(0.179)	(0.281)	(0.072)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7595	7595	7595	7595	5115	5115	7595	7595
IV	Jackknife	Jackknife	Jackknife	Jackknife	Jackknife	Jackknife	DOJ	DOJ
Range IV	All	All	± 15	± 15	± 15	± 15		
Adjusted R-squared	0.045	0.047	-0.754	-1.917	-0.221	-0.783	-0.536	0.104
F stat	14.12	14.29	3.12	2.61	5.46	3.74	2.57	4.21
Weak-IV Anderson-Rubin test, p-value	0.002	0.001	0.002	0.001	0.003	0.003	0.015	0.020

Note: Monthly data from 2010 to 2022. The sample includes all states except for Alaska and Mississippi, for which there is no information on VC crypto activity. The entries denote the second-stage coefficients of a panel-IV regression where $\text{CRegIn}_{s,t}$ is instrumented with the one period lag of the out-of-state average of CRegIn over all states in columns (1)–(2), and the states that rank 15 positions above and below s in the ranking of total venture capital raised for the period 2000–2009 in columns (3)–(6). The instrument in columns (7)–(8) is the one period lag of the natural logarithm of the amount of grants awarded by the US Department of Justice, Officer of Justice Programs in each state ie DOJ $\text{grants}_{s,t-1}$. Fin Hub is an indicator variable that takes value one for states with aggregate sectoral GDP for the Finance and Insurance sector for the period 2000–2009 above the median of the distribution in columns (1)–(4) and (7)–(8); for columns (5)-(6) it denotes if the state is on the top tercile vs those in the bottom tercile. Standard errors in parentheses are clustered by state: * $p < .10$; ** $p < .05$; and *** $p < .01$.

The coefficients from Table A1 are positive and statistically significant for financial hub states and negative and/or non-statistically significant for non financial hub states.[33] The estimates for the IV coefficients are larger in magnitude than those of the OLS, suggesting that our OLS coefficients are biased downwards, potentially due to omitted variable bias arising from confounding factors varying at the state-time level.[34]

33 To address the concerns about the robustness of our inference potentially stemming from a weak instrument, we report the weak IV Anderson-Rubin test, which supports the robustness of our results. For further details see Andrews I, and Stock JH. 2018. Weak Instruments and What To Do About Them or Andrews et al. 2019. Table A2 report the results of the corresponding first stage regressions.

34 For example, state-level legislation (such as environmental or remote working regulation) can be passed in batches. If several regulatory changes take place in a state, our index could capture some of that variation.

Table A2: Regulatory comprehensiveness and deal-making activity: first stage

	(1) $\text{CRegIn}_{s,t}$	(2) $\mathbb{1}\,[\text{Fin Hub}_s] \times \text{CRegIn}_{s,t}$	(3) $\text{CRegIn}_{s,t}$	(4) $\mathbb{1}\,[\text{Fin Hub}_s] \times \text{CRegIn}_{s,t}$	(5) $\text{CRegIn}_{s,t}$	(6) $\mathbb{1}\,[\text{Fin Hub}_s] \times \text{CRegIn}_{s,t}$	(7) $\text{CRegIn}_{s,t}$	(8) $\mathbb{1}\,[\text{Fin Hub}_s] \times \text{CRegIn}_{s,t}$
$\overline{\text{CRegIn}_{j\neq s,t-1}}$	-47.246***	-32.411***	-0.761	-1.063**	-1.298**	-1.560***		
	(0.124)	(5.276)	(0.467)	(0.445)	(0.535)	(0.527)		
$\mathbb{1}\,[\text{Fin Hub}_s] \times \overline{\text{CRegIn}_{j\neq s,t-1}}$	-0.007	0.979***	0.063	1.027***	-0.052	0.976***		
	(0.006)	(0.119)	(0.254)	(0.221)	(0.292)	(0.257)		
$\ln(\text{DOJ grants})_{s,t-1}$							0.018	-0.030
							(0.026)	(0.021)
$\mathbb{1}\,[\text{Fin Hub}_s] \times \ln(\text{DOJ grants})_{s,t-1}$							-0.002	0.090***
							(0.023)	(0.019)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7595	7595	7595	7595	5115	5115	7595	7595
Range IV	All	All	± 15	± 15	± 15	± 15		
Adjusted R-squared	0.988	0.893	0.681	0.696	0.696	0.711	0.677	0.619

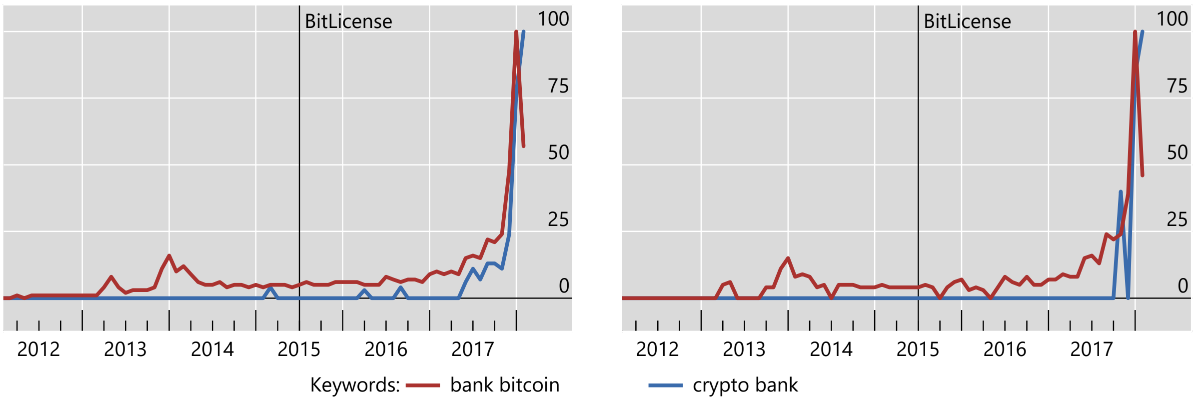
NOTE: Monthly data from 2010 to 2022. The sample includes all states except for Alaska and Mississippi, for which there is no information on VC crypto activity. The entries denote the first-stage coefficients of a panel-IV regression where $\text{CRegIn}_{s,t}$ is instrumented with the one period lag of the out-of-state average of CRegIn over all states in columns (1)–(2), and the states that rank 15 positions above and below s in the ranking of total venture capital raised for the period 2000–2009 in columns (3)–(6). The instrument in columns (7)–(8) is the one period lag of the natural logarithm of the amount of grants awarded by the US Department of Justice, Officer of Justice Programs in each state ie DOJ $\text{grants}_{s,t-1}$. Fin Hub is an indicator variable that takes value one for states with aggregate sectoral GDP for the Finance and Insurance sector for the period 2000–2009 above the median of the distribution in columns (1)–(4) and (7)–(8); for columns (5)-(6) it denotes if the state is on the top tercile vs those in the bottom tercile. Standard errors in parentheses are clustered by state: * $p < .10$; ** $p < .05$; and *** $p < .01$.

Overall, our findings are consistent with a more comprehensive regulatory environment in a nascent sector being conducive to the funding of innovative firms, rather than constraining it, but only in states where the financial system is well developed. The results signal that there is a role for public intervention in the VC market to promote and sustain the growth of start-ups.

B Additional robustness

Figure B1: **Regulation impact and traditional financial institution entry**

(a) Search interest in the United States (b) Search interest in the state of New York



NOTE: The graph shows the Google Trends search interest for the keywords "bank bitcoin" and "crypto bank" in the United States (left) and in the state of New York (right).
SOURCE: Google Trends.

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