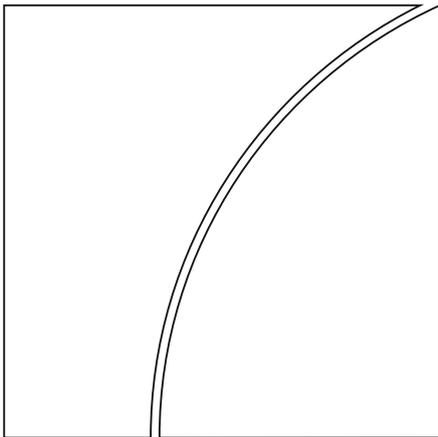




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Regulatory sandboxes and fintech funding: evidence from the UK

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Regulatory Sandboxes and Fintech Funding: Evidence from the UK

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Abstract

Over 50 countries have introduced regulatory sandboxes to foster financial innovation. This paper conducts the first evaluation of their ability to improve fintechs' access to capital and attendant real effects. Exploiting the staggered introduction of the UK sandbox, we establish that firms entering the sandbox see an increase of 15% in capital raised post-entry. Their probability of raising capital increases by 50%. Sandbox entry also has a significant positive effect on survival rates and patenting. Investigating the mechanism, we present evidence consistent with lower asymmetric information and regulatory costs.

JEL Codes: G24, G38, M13, O38.

Keywords: regulatory sandbox, fintech, start-ups, venture capital, innovation.

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1. Introduction

The rapid growth of innovative companies in the financial sector that use new technology holds the promise of spurring competition, leading to efficiency gains and more choice for consumers. However, ‘fintechs’ offer novel products in an environment of high regulatory uncertainty, so they often struggle to raise enough capital to develop products and expand ([Haddad and Hornuf, 2019](#)). Policymakers around the world are thus stepping up their efforts to foster innovation in the financial sector, as they have done with business accelerators or grants in other areas ([Howell, 2017](#); [González-Uribe and Leatherbee, 2018](#)).

A landmark initiative to nurture fintechs was the creation of the “regulatory sandbox” by the United Kingdom’s Financial Conduct Authority (FCA). Established in November 2015, the sandbox offers fintechs a controlled testing environment in which they can try out their products on a limited set of customers. Testing occurs under close regulatory supervision: firms receive advice to help them navigate the complexities of regulations and to ease the route to authorisation. A key objective of sandboxes is to foster innovation by facilitating fintechs’ access to financing at early stages of development.¹ Regulators can use sandboxes to learn about new financial technologies and emerging trends, as well as to identify associated risks before products are launched for the mass market.

By now, over 50 countries have followed the UK and introduced their own regulatory sandbox, often with the goal of nurturing the fintech sector ([Wechsler et al., 2018](#)).² And yet, despite their wide-spread adoption and significant attention in the media and policy circles, little systematic empirical evidence exists on whether sandboxes actually help fintechs to raise funding, innovate, or develop viable business models. Nor is there any evidence on the underlying channels that could be at work.

This paper analyses how entering the FCA’s regulatory sandbox affects fintechs’ abil-

¹See [Regulatory sandbox – Financial Conduct Authority](#): “A regulatory sandbox has the potential to deliver more effective competition in the interests of consumers by [...] enabling greater access to finance for innovators”.

²At the time of writing, 57 jurisdictions operate one or more sandboxes. See the World Bank’s [Key Data from Regulatory Sandboxes across the Globe](#) for current numbers.

ity to raise funding and attendant real effects. We collect data on capital raised by fintechs in the UK sandbox for the period from 2014q1 to 2019q2. Detailed deal-level data, broken down by individual investor, as well as background information on a firm’s age, size, industry, location, and its CEOs allow us to investigate different channels through which the sandbox could affect a firm’s access to capital. We focus on the sample of firms accepted into the sandbox and exploit the fact that these firms entered the sandbox in five cohorts. As entry is staggered over rounds of six months, we can compare a firm’s capital-raising activity before and after participation in the sandbox, relative to firms that will enter the sandbox later.

Entry into the sandbox is associated with an increase in the average amount of funding raised and a higher probability of raising funding. In firm-level regressions, we find that entry into the sandbox is followed by a 15% increase in capital raised (or \$700,000) over the following two years, relative to firms that will enter the sandbox at a later date. Firms’ probability of raising capital increases by 50%. The increase in capital raised corresponds to about one standard deviation.³

We obtain similar findings when we compare sandbox fintechs to a set of matched control firms. Specifically, using a coarsened exact matching approach, we select a sample of fintechs that are statistically similar in terms of observable firm characteristics. We estimate a difference-in-differences specification with firm and time fixed effects, comparing firms that enter the sandbox to those that never enter the sandbox, but share similar characteristics. In the matched sample, we find almost identical effects to our baseline strategy: entry into the sandbox is associated with a relative 15.1% increase in capital raised.

Facilitating fintechs’ access to finance is an important step in benefitting consumers through greater innovation and competition. While the short time span since its inception does not allow for an evaluation of the sandbox’s effects on the consumer surplus or competition in the financial sector yet, we can analyse survival rates and patenting

³The magnitude of our estimates is in line with findings on the effectiveness of public policy to foster innovation in other settings. [Howell \(2017\)](#) finds that R&D grants roughly double a firm’s chance of receiving venture capital investment. For the UK, [Bone et al. \(2019\)](#) find that accelerators increase firms’ fundraising activity by around 75%.

activity. We find that sandbox firms are significantly more likely to still be in operation today, compared to a set of matched control firms that did not enter the sandbox (75% vs 60%).⁴ In addition, sandbox entry is associated with an increase in patenting activity, suggesting that easier access to capital spurs firms' innovative activity.

We then investigate the underlying mechanisms. Asymmetric information is particularly acute in venture capital markets, because issuers are mainly early-stage firms with no prior track records (Trester, 1998). Uncertainty about the quality of new products and services offered by fintechs could thus present a serious obstacle to raising capital – especially in an environment of high regulatory uncertainty (Haddad and Hornuf, 2019). Navigating the complexities of a constantly changing regulatory framework could further pose a significant cost to firms. Sandboxes could curb informational frictions through regulatory oversight and continuous dialogue between firms and the regulator during the testing period that offers reassurance to investors that firms meet their regulatory obligations. Additionally, advice by trained case officers promises to lower regulatory costs for firms and reduce the risk to firms of offering products that could be in violation of the regulatory framework.

Our evidence is consistent with the notion that the sandbox reduces information asymmetries between investors and firms, as well as costs associated with regulatory uncertainty. We first show that the estimated positive effect of sandbox entry on capital raised is stronger for smaller and younger firms, which are more opaque and hence subject to severe informational frictions (Hall and Lerner, 2010). Similarly, entry into the sandbox is associated with greater increases in deal volume for venture capital deals, which are generally more information-sensitive, compared to other types of deals (Gompers, 1995; Howell, 2020). Second, data at the investor-firm level show that firms in the sandbox raise more capital especially from investors based outside the UK and investors that have not previously invested into the firm. Since these investors likely face higher information asymmetries (Grinblatt and Keloharju, 2001; Ivković and Weisbenner, 2005),

⁴These patterns are in line with preliminary findings by the FCA (2019), which reports that around 80% of firms that successfully tested in the sandbox are still in operation (as of 2019), which is significantly higher than average numbers for startups. For example, the three-year survival rate of startups averages around 60% (Hyytinen et al., 2015).

we interpret this finding as evidence that the sandbox helps in reducing informational frictions. Finally, we show that firms with a CEO who has a background in financial law raise relatively less capital after entry into the sandbox. This is in line with anecdotal evidence that CEOs without prior experience in financial regulation benefit the most from the guidance provided by case officers (Deloitte, 2019), and thereby from the reduction in regulatory costs and uncertainty.

A key challenge for identification is that even among the group of firms that enter the sandbox at some point, the entry date could be correlated with unobservable firm characteristics.⁵ We perform a number of exercises to address this concern. First, we show that among the group of firms that enter the sandbox at some point, the specific entry date is uncorrelated with observable firm characteristics. Second, our main results hold when we compare sandbox fintechs to a set of control firms that are similar along observable characteristics to the sandbox firms, selected via coarsened exact matching. Third, we show that our results are robust to the inclusion of fixed effects. For example, in investor-firm level regressions we include investor*firm and firm*time fixed effects. These fixed effects account for unobservable heterogeneity within each firm-investor combination, as well as unobservable time-varying factors at the firm level (Khwaja and Mian, 2008; Jiménez et al., 2014). While results from these tests suggest that the sandbox has helped fintechs raise funding, in interpreting our findings it is important to keep the caveat in mind that sandbox entry is not random.

We provide a series of additional exercises. One explanation for our findings could be that investors simply learn about firms as they gradually reveal their quality to the market over time, irrespective of entry into the sandbox. Then, firms' ability to raise funding would increase gradually. If instead investors learn about the quality of a firm because of the "sandbox certification", firms' ability to raise funding will increase immediately after entry. We find that the strongest effects on funding raised occur in the first two

⁵For example, even within the group of firms that enter the sandbox, the entry date could be correlated with a change in the quality of the offered product or service. Such life-cycle considerations imply that firms could then have raised more capital irrespective of their entry into the sandbox. Likewise, firms could strategically postpone their capital raising activity until acceptance into the sandbox, possibly in the hope of raising additional capital.

to four quarters upon entry. Four to eight quarters after entry, the sandbox still has a positive, but smaller effect on funding raised. We also show that our results are robust to alternative estimation methods to account for the presence of zeros in our dependent variable, or when we include cohort or contiguous-cohort fixed effects.

Our findings do not preclude that the sandbox operates through additional channels. For example, it could have a general signaling effect: selection into the sandbox could serve as a stamp of approval and help sandbox firms raise more capital. Regulatory approval could further indicate that a firm's product is viable and will face fewer regulatory hurdles going forward. From the firm's perspective, this would mean that it now has the approval to sell its products, which likely requires investments in sales and scaling. If so, entering (and graduating from) the sandbox would lead to higher demand for capital among all sandbox firms. That said, our findings on the differential effects for small and young firms, and especially the larger effects found for capital raised from foreign and first-time investors, are consistent with the sandbox reducing informational frictions and facilitating fintechs' access to capital above and beyond its general effects through signaling and on the demand for funding.

All in all, our findings suggest that the regulatory sandbox improves fintechs' access to capital; firms entering the sandbox are also more likely to still be in operation and have a patent. To the best of our knowledge, this paper provides the first systematic evidence that sandboxes help fintechs to raise capital and innovate – and hence achieve one of their explicit goals. Sandboxes, which have already been widely adopted, could hence become a useful policy tool for harvesting the benefits of financial innovation.⁶

Our paper contributes to the debate on how public policies can foster innovation (Kerr and Nanda, 2015; Lerner and Nanda, 2020). A recent literature has established that fintechs face serious obstacles to raising capital (Block et al., 2018; Haddad and Hornuf, 2019), despite the fact that their innovation provides value to innovators and investors (Chen et al., 2019). As market failures can lead to sub-optimal private-sector expenditure on research and development, public policies to foster innovation, for example

⁶Cross-country evidence suggests the establishment of a sandbox is followed by a surge in fintechs' capital raising activity (Cornelli et al., 2021). These correlations are in line with our main findings.

through grants and business incubators or accelerators, can have sizeable benefits (Howell, 2017; González-Uribe and Leatherbee, 2018; Yu, 2020; González-Uribe and Reyes, 2021).⁷ Policy makers hence want to promote innovation in the financial sector, and regulatory sandboxes have emerged as a prominent tool to do so. Yet, evidence on their effectiveness is scarce.

We also relate to literature that investigates how to regulate fintechs (Arner et al., 2017; Zetzsche et al., 2017; Magnuson, 2018). Buchak et al. (2018) show that the rapid growth of fintech lenders in the US is mostly explained by lighter regulation and better technology, with benefits to consumers (see also Thakor (2020) and Fuster et al. (2019)). Other studies show that the use of big data and machine learning can lead to algorithmic discrimination and changes in consumer behaviour (Bartlett et al., 2019; Berg et al., 2020; Fuster et al., 2022), and that the growth of fintechs raises concerns about data privacy (Armantier et al., 2021; Chen et al., 2023; Doerr et al., 2023). The entry of fintechs into finance thus constitutes a dilemma for policy makers: they need to promote innovation in the financial sector, but without compromising data privacy, financial stability or consumer welfare (Brummer and Yadav, 2019). New regulatory tools might thus be needed, and sandboxes could be one such tool: they provide regulators with the ability to support safe innovation by gauging the potential welfare implications of new products before they are launched. An assessment of the effectiveness of sandboxes and an understanding of the channels through which they operate is hence indispensable.

The remainder of the paper is organized as follows. Section 2. provides background information on the UK regulatory sandbox. Section 3. gives an overview of our data and sample of fintechs. Section 4. explains our empirical strategy. It then reports the main results and provides evidence on the mechanisms at work. In Section 5. we present robustness tests. Section 6. concludes.

⁷Brown and Davies (2020) show that early-venture fundraising can be inefficient if information acquisition is costly, leading entrepreneurs to undertake bad projects and forgo profitable ones.

2. The UK Regulatory Sandbox

The UK, and especially London, has become a global fintech hub. Over the last decade, fintech start-ups raised around one-fifth of their worldwide funding in the UK. This number is topped only by the US, where fintechs raise almost half of global funding. Notably, the UK increased its share from less than 15% in 2010-2014 to over 20% for the 2015-2019 period. It thereby overtook China in terms of volume. However, despite these encouraging numbers, fintechs still face severe obstacles in raising capital (HM Treasury 2016; 2019). Since access to capital is crucial for young firms with high growth potential, its scarcity threatens to slow innovation in the financial sector.

Partly in response to these worries, the Financial Conduct Authority announced the world's first regulatory sandbox as part of its "Project Innovate" in 2015 (FCA 2015). The sandbox operates on a cohort basis with two six-month test periods per year. Between November 2016 and July 2019 (the end of our sample period) five cohorts of firms have been accepted into the sandbox on the following dates: 7 November 2016, 15 June 2017, 5 December 2017, 3 July 2018, and 29 April 2019.⁸ In total, 375 firms have applied and 118 have been accepted into the FCA sandbox. Each cohort averages around 25 firms. Crucially for our setting, the introduction of the sandbox was not accompanied by stricter regulation for non-sandbox firms that could have discouraged them from seeking financing, or mechanically benefited sandbox firms. Nor does the FCA provide insurance, in the sense that customers of sandbox firms are protected from any risks arising from using their products and services.

The FCA publishes the names of accepted firms for each round of the sandbox; it does not make the list of rejected firms available. The average firm in the sandbox is a start-up or small and medium enterprise in retail banking (including payments), wholesale markets, retail and wholesale investment and lending, or insurance propositions. Sandbox firms offer a wide array of new products and services. For example, firms offer a

⁸We restrict our analysis to cohorts one to five, as from cohort six onward, the FCA specified certain areas of innovation. For example, cohort six emphasized the topic of "make finance work for everyone and support the UK in the move to a greener economy", which could lead to selection effects.

platform that facilitates the securitization of SME debt by digitising credit applications; an interest-free salary-advance and cash flow management product utilising distributed ledger technology; or an aggregation platform that facilitates investment in a diversified portfolio of P2P loans.

The ‘sandbox process’ contains four distinct steps: application, selection, testing and exit. The FCA selects firms out of the pool of applicants based on whether the firm offers a genuine innovation that benefits UK consumers. The innovation should constitute an improvement over existing products and services, and hence promote competition.⁹ The age, size or profitability of a company is not an eligibility criteria, start-ups and incumbent are equally encouraged to apply. Firms that fulfil these requirements and for which the FCA’s input is deemed useful (‘need for support criteria’) are selected into the sandbox. Firms are assigned a dedicated case officer who helps to design the test setup, provides guidance to complete the necessary paperwork for authorisation, and helps firms navigate the regulatory environment throughout the process.¹⁰

Once firms are granted authorisation, they test their products in a limited market environment. Specifically, successful applicants set up their capabilities subject to regular reporting requirements to monitor how the technology is evolving and how the business is meeting its compliance targets. In this phase, firms have to familiarize themselves with the regulation with the help of case officers. After six months, firms submit a final testing report and exit the sandbox. They can apply for a permanent authorisation upon completion.

One of the main objectives of the sandbox is to attract investments toward fintechs (FCA 2015). In the words of the FCA, “the potential benefits of a regulatory sandbox could be significant from better access to finance. Financial innovation relies on invest-

⁹Further requirements are that the firm possesses well-developed testing plans, including clear acceptance criteria, or that there are sufficient safeguards in place to protect the consumers and to provide redress in case of need. Firms that offer the following services are not eligible: deposit taking, insurance underwriting, and multilateral trading facilities.

¹⁰For example, case officers help the selected firms to design and implement the tests, ensuring that appropriate safeguards are embedded in products under revision; they highlight the regulation relevant for the company; and facilitate engagement with FCA subject matter experts, possibly reducing the expenditures on external regulatory consultants and helping firms better understand how they fit in the current regulatory framework.

ment, much of it through equity funding. Regulatory uncertainty at a crucial growth stage means that FinTech firms find it harder to raise funds and achieve lower valuations as investors try to factor in risks that they are not well placed to assess”.¹¹

These arguments are in line with the finding that asymmetric information is particularly acute in venture capital markets, because issuers are mainly early-stage firms with no prior track records (Trester, 1998; Howell, 2020). Resolving information problems in such an environment requires that investors engage in an intensive and costly up-front screening and post-investment monitoring. The inherent uncertainty about the quality of new products and services offered by fintechs thus presents a serious obstacle to raising capital (Haddad and Hornuf, 2019).

Sandboxes could further curb informational frictions through regulatory oversight during the testing period. Continuous dialogue between firms and the regulator offers reassurance to investors that firms meet their regulatory obligations. In the UK context, adverse selection is potentially reduced because the FCA claims to select firms that offer genuine innovation with clear benefits to consumers. Moral hazard may also be reduced if close supervision by the FCA spurs firms to improve their governance and adopt more rigorous policies and processes.

Besides information problems, another critical obstacle to capital access relates to regulatory costs and uncertainty. Regulatory uncertainty discourages investment because investors are hesitant to invest in a firm that is offering products whose regulatory framework is unclear. Even innovative and successful companies might be forced to alter their business model to comply with continuously evolving regulations. According to the World Bank’s *Doing Business* report, regulatory restraints are a key barrier to innovation.¹² The sandbox could reduce regulatory uncertainty, as regulators throughout the process are able to collect information on new products, identify new risks, and accordingly adapt existing or introduce new regulation swiftly. Advice by trained case officers promises to lower regulatory costs for firms and reduce the risk to firms of offering

¹¹See [Regulatory sandbox – Financial Conduct Authority](#).

¹²In a 2020 survey by software provider Finastra, among over 750 fintech companies, only 4% of companies believe that there are no barriers to innovation from existing regulation; and almost half of respondents state that regulation is too tight.

products that could be in violation of the regulatory environment going forward.

Anecdotal evidence suggests that the sandbox has delivered value to firms (Deloitte, 2019). For example, companies value the guidance on the application of regulation to innovative products and services, and highlight the benefits of detailing the risks relating to their business mode to the regulator. They further report that operating their technology successfully in a live and regulated environment helps them to signal credibility to investors. Firms further state that the route to authorisation is significantly simpler and faster when regulation is considered from the start and with the help of case officers (FCA 2019).

Enhancing fintechs' access to capital is an explicit goal of sandboxes. A complementary long-term policy objective is to increase consumer welfare, for example by promoting competition and innovation while ensuring financial stability. The short time span since their inception does not allow us to evaluate these long-term effects. However, our paper empirically tests whether the UK sandbox helps fintechs to raise capital, and whether there are any effects on survival rates and patenting activity – thereby providing a first step in assessing sandboxes' usefulness.

3. Data Description and Sample Selection

PitchBook provides detailed data on capital raised at the deal level and is one of the most comprehensive sources of investment data for the fintech sector. We obtain data on all individual deals of the sandbox firms, as well as deals for a random sample of around 1,400 control firms (more below), over the period 2014q1 to 2019q2. For each deal, PitchBook records detailed characteristics such as issuer name, deal date, deal amount, and type/purpose of the deal. Further, each deal contains information on the individual investors and their location. The main types of deals are venture capital (VC) deals (including accelerators, incubators, seed, and angel deals), private equity (PE) deals (mainly for growth/expansion), and restructuring deals (including deals for mergers and acquisitions and buyout deals). VC, PE and restructuring deals represent around 63%, 7%, and 17% of the total number of deals.

We further collect any available information on the history of each company and the biography of the CEO (or founder). We obtain the year the company was founded, its primary industry classification, and the current business status (start-up, generating revenue/profitable, other). We also record the city where the company is headquartered. Information on the CEO includes gender, educational background, and occasionally the year of graduation. Finally, we collect information on the identity of each investor participating in a deal, as well as the size of each investor’s total portfolio. We also observe the country where the investor is headquartered, which allows us to separately investigate the behaviour of foreign and UK-based investors. PitchBook also provides information on whether an investor is a new/first-time investor in the issuing firm.

Sandbox firms. The main analysis focuses on firms that enter the sandbox in one of the five cohorts during the sample period. We manually identify sandbox firms in the PitchBook database, using the name and description of the company provided by the FCA. Out of the 118 firms that have been accepted into the sandbox, we are able to identify 106 in the PitchBook database.

We perform a series of steps to clean and prepare the data. First, seven firms entered the sandbox more than once. To avoid double-counting, for these firms we set the entry date at the date when they entered the sandbox for the first time. Second, we drop deals that report no time of deal (36 deals), since it is not possible to determine whether they took place before or after sandbox entry. Third, we drop observations with missing or zero deal size (83 deals). Finally, firms must report their primary industry, location, CEO gender, and founding date (these are the items with reasonably consistent coverage).¹³

We then aggregate our deal data, which is at daily frequency, to the quarterly level. Since the focus of our analysis is on fintech start-ups, the baseline specification excludes sandbox firms that are (or belong to) large or listed firms and therefore do not report accounts or do not raise capital separately from the parent (eight firms, for example

¹³While it could be the case that more successful firms also have better data coverage, our analysis of data on survival rates does not bear this out. Comparing survival rates among sandbox firms for which all data items are populated to those with missing data items shows that 77% of sandbox fintechs with good data coverage are (as of 2022q1) still in operation, compared to 74% for those with insufficient data coverage.

Lloyds or HSBC). However, we will include these larger firms when we investigate the mechanism. Finally, we trim log deal volume at the 1st and 99th percentile to keep outliers from driving our results. To create a balanced panel, we replace missing firm-quarter observations with zeros and exclude all observations prior to a firm's founding year. We end up with a sample of 908 firm-quarter observations for 56 firms from 2014q1 to 2019q2.

Our main firm-level outcome variables are $\log(\text{deal amt})$, which equals the log of (1+total capital raised) by firm f in quarter t ; and dummy *capital raised*, which equals one if a firm raised any capital in a quarter, and zero otherwise. As main explanatory variable, for each firm we construct the dummy *post SB entry*, which takes on a value of zero before sandbox entry, and a value of one upon entry and thereafter. As firm-level controls, we use the log of (1+company age), the dummy *male*, which takes on a value of one if the CEO is male and zero otherwise, and a dummy that indicates whether or not a firm is based in London. We further collect information on CEOs' biographies to create the dummy *CEO has law degree*, which takes on a value of one if a CEO holds a degree in law or has previous experience with financial law. Further, we collect information on the number of total investors and the number of new investors per deal, as well as the share of UK-based, non-UK-based, and US-based investors.

To construct the investor-firm level panel, we collect data on all investors that take part in a given deal and then split deal volume across investors. Since we observe only the number of investors and the total deal size for each deal, we do not observe the individual amount invested by each investor. In the baseline estimation, we hence split total deal volume on a pro-rata basis. This is, if the deal size is \$100 and there are two investors, we assign \$50 to each investor. For robustness checks, we also split loan volume by investor 'size', measured by their total investments. For example, if the deal size is \$100 and there are two investors, one with aggregate investments of \$1500 and one with aggregate investments of \$500, we assign \$75 to the first and \$25 to the second investor. We also define the dummy *capital raised* that takes on a value of one if a given investor invests in a given firm in quarter t (the extensive margin), and zero otherwise. This approach is

insensitive to the chosen method of allocation.

Table 1, panel (a) reports descriptive statistics. There is significant variation in deal characteristics, with an average deal size of \$4.7 million and a standard deviation of \$27.5 million. Out of all firm-quarter observations, firms raise capital in 6.1% of all cases. Panel (b) shows that the median (average) firm is four (six) years old as of 2019. Some 75% of our firms are less than six years old, 52% of firms are based in London. The median and average firm has one CEO, and around four-fifth of CEOs are male. The average CEO graduation year is 1998. The average deal has around 1.8 investors (with a maximum of 11), and 1.7 new investors (with a maximum of 10). When capital is raised, the average share of investors based in the UK is around 60%. Out of the 40% of foreign investors, roughly half are US-based.

Control firms. To contrast the performance of sandbox firms with that of similar firms that never enter the sandbox, we collect PitchBook data on a random sample of over 1,400 fintechs with around 3,000 deals between 2014q1 and 2019q2. For these firms, we collect information on deal size and date, as well as on age, CEO gender, location, industry, and business status. We then use a coarsened exact matching (CEM) approach to select a suitable sample of control firms for our sample of sandbox firms (Blackwell et al., 2009). CEM creates matches between the treated (sandbox) and control firms (non-sandbox), based on the set of controls: age, CEO gender, location, industry, and business status. Controls are coarsened to maximize balance of the matched data set and ensure that most treated observations have a match (Iacus et al., 2012). The final sample consists of 54 sandbox firms matched to 158 control firms. Out of our 908 sandbox observations, 24 observations (two firms) result in no match. The total sample of treated and matched control firms contains 3,779 firm-quarter observations and is balanced in terms of observable firm characteristics. Note that while the FCA does not make public the list of rejected firms, they could be part of our control sample.

Real outcomes. We collect two indicators to assess the real effects of participating in the sandbox: first, a dummy indicating whether a firm failed as of 2022q1; and second, whether a firm had any patents granted in a given quarter. Survivorship status is obtained

from the Companies House database, which is accessible online. For 198 out of the 212 sandbox and controls firms we could identify the survivorship status. We classify all firms flagged as dissolved, dormant, or liquidated as ‘failed’. We obtain the number of patents granted from Pitchbook, resulting in 862 firm-year observations among sandbox firms. [Table 1](#), panel (a) reports summary statistics and show that the average probability for a sandbox firm to have a patent granted in a given quarter is 1.8%. 36% of firms failed. Among sandbox firms only 25% failed, while around 40% of the control firms failed.

4. Empirical Strategy and Results

This section explains our empirical strategy and presents the main results. We first show that sandbox entry is associated with an increase in capital raised, as well as increased survival rates and patenting activity. Investigating the mechanism, we find that effects are stronger for younger and smaller firms, as well as for foreign or first-time investors, and firms with a CEO without prior experience in financial regulation – suggesting that the sandbox reduces informational frictions and regulatory costs.

4.1 Sandbox Entry and Capital Raised

How does entry into the regulatory sandbox affect firms’ ability to raise capital? To address this question, we first focus on the group of firms within the sandbox. In a second step, we compare firms that entered the sandbox to firms that never entered the sandbox, but are statistically similar in terms of observable firm characteristics. For this exercise, we focus on the set of sandbox and non-sandbox companies matched via coarsened exact matching.

To investigate the relation between entry and capital raised among the sample of fintechs in the sandbox, we exploit its staggered design: firms enter in different cohorts. The identifying assumption is hence that among the group of firms that join the sandbox during the sample period, a firm’s observable and unobservable characteristics are not systematically correlated with its entry date.

To test this assumption, [Table 2](#) shows results of firm-level regressions with different

firm characteristics as outcome variable. As explanatory variables, we include dummies for each cohort, where *sandbox cohort 1* is the reference group. Column (1) shows that there are no systematic differences in firm age across cohorts. Column (2) shows that – except for the fifth cohort – firms are not significantly more or less likely to be from London in later cohorts. Column (3) shows that whether a firm reports that it is already generating revenue or not does not differ across cohorts either. Column (4) uses a dummy with a value of one for companies with at least one male CEO and column (5) the number of CEOs as dependent variable. With the exception of cohort three, which is significantly more likely to have a male CEO, there are no statistically significant differences. In column (6) we use the firm fixed effects resulting from a regression of log deal amount on firm fixed effects as dependent variable. The fixed effects reflect all observable and unobservable time-invariant firm-level variation that is correlated with the amount raised. There is no significant correlation with the firm’s respective cohort.

While selection into the sandbox is not random – after all, the FCA aims to accept firms that offer an innovative product – [Table 2](#) suggests that *within* the group of firms that enter the sandbox, the exact entry date is not systematically correlated with observable firm characteristics. These facts mitigate concerns that our results are explained by omitted variables or selection effects. And yet, the firm-level analysis cannot rule out that unobservable time-varying factors at the investor or firm level confound our estimates. To address this concern, we compare sandbox firms to a sample of matched control firms (see below); and estimate investor-firm level regressions in [Section 4.3](#) to show that controlling for observable and unobservable time-varying firm characteristics through granular fixed effects does not affect our estimates.

To analyse how entry into the sandbox affects firms’ ability to raise capital, we estimate the following regression at the firm-quarter level:

$$y_{f,t} = \beta \text{ post SB entry}_{f,t} + \text{controls}_f \times \text{ post SB entry}_{f,t} + \theta_f + \tau_t + \varepsilon_{i,t}. \quad (1)$$

The dependent variable is either the logarithm of 1 plus the total deal amount for firm f in quarter t ; or the dummy *capital raised*, which takes a value of one if the firm raises

capital in a given quarter.¹⁴ The dummy *post SB entry* takes a value of one after sandbox entry, and zero for all quarters prior to entry. We further include a vector of time-invariant firm characteristics, interacted with the post dummy: log firm age in 2019, CEO gender, and a dummy for being headquartered in London. We cluster standard errors at the firm level to account for serial correlation. In some specifications we include fixed effects. Firm fixed effects (θ_f) control for unobservable time-invariant firm characteristics, such as industry or location. Time fixed effects (τ_t) control for common trends. To control for unobservable time-varying shocks common to all firms within an industry, we occasionally include industry*time fixed effects instead of time fixed effects.

Including firm fixed effects in Equation (1) represents a difference-in-differences specification: We compare firms that entered the sandbox at time t to firms that have not yet entered the sandbox at t , holding unobservable firm characteristics constant. Coefficient β hence indicates whether firms that enter the sandbox raise more or less capital, relative to firms that do not enter the sandbox at time t . If the sandbox facilitates firms' access to capital, we expect $\beta > 0$.

The identification assumptions are *i*) that absent treatment, firms that enter the sandbox at time t would follow the same trend in capital raised as firms that enter the sandbox at a later date (parallel trends), and *ii*) that funding raised by one firm does not affect the funding raised by another firm (Stable Unit Treatment Value Assumption, SUTVA). We provide direct evidence on parallel trends below. With regard to SUTVA, the focus of our analysis is on a set of relatively small fintech firms. Arguably, even a sizeable increase in capital raised by one of these firms would not deplete the amount of total capital available for other firms. For example, total venture capital investment in the UK stood at around £3.8bn in 2016. The average deal volume in our sample represents only a small fraction of this total.

Before moving to the regression analysis, panel (a) in [Figure 1](#) provides non-parametric evidence that firms raise more capital after entering the sandbox. The horizontal axis

¹⁴To address the concern that a transformation of the form $\log(1 + x)$ could lead to a bias in the measurement of the dependent variable, we confirm that all our main results hold when we use an inverse hyperbolic sine transformation (unreported).

plots the time dimension. A value of zero denotes the date at which a firm enters the sandbox, and the axis ranges from 8 quarters before to 12 quarters after sandbox entry. The vertical axis shows the total funding raised per quarter (left axis), as well as the cumulative funding raised (right axis). The amount of capital raised increases sharply around time zero when firms enter the sandbox. The increase in capital raised is particularly pronounced in the first year upon entry, and tapers off after around ten quarters.¹⁵

We now investigate this pattern in greater detail. Table 3 reports the results of Equation (1) over our sample period. In columns (1) to (4), we estimate the effect of the sandbox at the intensive margin for the treated sample and use the log deal amount as dependent variable. Column (1) includes firm-level controls and shows that firms that enter the sandbox raise 9.3% more capital than firms that have not (yet) entered the sandbox. When we add firm fixed effects in column (2), the coefficient increases in size and statistical significance. Adding time fixed effects in column (3) leads to a further increase in the coefficient. Conditional on unobservable time-invariant firm characteristics and common shocks, firms see an increase in deal amount by about 14.8% after entering the sandbox, relative to firms that did not enter the sandbox. Evaluated at the average deal, this represents an increase in capital raised of \$700,000. Finally, in column (4) we add industry*time fixed effects.¹⁶ The coefficient remains significant at the 5% level and similar in magnitude to column (3).

In columns (5) and (6) we explore the effect of the sandbox at the extensive margin. The outcome variable is the dummy *capital raised*, so we estimate logistic regressions. Column (5) includes firm controls; column (6) adds firm and time fixed effects. Both columns report average marginal effects. The estimated effects are economically large and statistically significant: the probability of raising capital increases by 3.1 percentage points upon sandbox entry, relative to an average 6.1% probability of raising capital in a given quarter. In other words, entry into the sandbox is associated with an increase of

¹⁵Some firms know about their acceptance into the sandbox already a few months before their official entry. Some firms could disclose their still-informal relationship with the FCA to investors, which could explain the modest increase in funding occurring between $t = -1$ and $t = 0$.

¹⁶Note that including industry*time fixed effects results in a loss of observations, as not all industries contain two firms in a given year.

about 50% in the probability of raising capital.

Firms entering the sandbox in earlier cohorts could behave systematically different from later entrants prior to entry. To investigate whether there were any potential pre-trends across groups, we include a set of dummy variables in the baseline regression to trace out the quarter-by-quarter effects of sandbox entry on the logarithm of (1+deal amount):

$$\log(1 + amt)_{f,t} = \sum_{k=-4}^{K=12} \beta_k SB_{f,k} + \theta_f + \tau_t + \varepsilon_{f,t}. \quad (2)$$

Dummy variables ‘SB’ equal one in quarter k before or after sandbox entry. The omitted category is $k = 0$ and corresponds to the date of sandbox entry of firm f . Coefficient β_k is the estimated change in deal amount k quarters before or after entry. θ_f and τ_t denote firm and time fixed effects, standard errors are clustered at the firm level. [Figure 1](#), panel (b) plots coefficients β_k and corresponding 90% confidence intervals. Average deal volume is significantly higher already in the first quarter after entry. The positive estimated effect of entry into the sandbox peaks in the third quarter (13%) and dissipates after around two years. There is no discernible pre-trend: firms that enter the sandbox in quarter t did not raise more capital before entry than firms that enter the sandbox at a later stage.

Matched control firms. Having established that sandbox entry is followed by an increase in firms’ capital raised when we focus on the firms that enter the sandbox at some date, we now use information on our set of non-sandbox control firms. In [Table 3](#), panel (b) repeats the estimations from panel (a), but for the sample of matched control firms. Each regression is weighted by the respective CEM weights to ensure balancedness in co-variates; the number of firm-quarter observations increases to 3,779. Coefficient β now indicates whether entry into the sandbox improves firms’ access to capital, relative to firms that never enter the sandbox but that are similar in terms of observable characteristics.

In panel (b) the estimated coefficients are similar in terms of sign, size, and significance to those in panel (a). In our most-stringent specification with firm and industry*time fixed effects in column (4), entry into the sandbox is followed by an increase in capital

raised by 15.1% in panel (b) vs. 15.0% in panel (a). The probability of raising capital increases significantly as well, by around 3.3 percentage points (or 50%, relative to the mean) in the most conservative specification in column (6).

In conclusion, [Table 3](#) shows that entry into the sandbox is followed by a statistically significant and economically large increase in capital raised and in the probability of raising capital.

4.2 Survival Rates and Innovation

While facilitating fintechs' access to finance is an explicit goal of the regulatory sandbox, it ultimately aims at promoting innovative companies and increasing consumer welfare. The short time span since their inception does not allow for an evaluation of the effects on the consumer surplus or financial stability yet. Nor is there systematic data available on firms' revenues, cash flow, or customer base. In what follows we hence investigate whether the sandbox has 'real' effects on survival rates and patenting activity.

[Figure 2](#), panel (a) plots average survival rates and shows that firms that have entered the sandbox are more likely to still be in operation, compared to the sample of matched firms with similar characteristics. While the share of fintechs that are still in operation equals around 60% for those that did not enter the sandbox, it equals around 75% for our sample of sandbox fintechs.

Sandbox firms exhibit higher survival rates also when we control for firm characteristics, as shown in panel (a) of [Table 4](#). We estimate standard cross-sectional logistic regressions, where the dependent variable is a dummy with a value of one if a firm failed, and zero otherwise. The independent variable is the dummy *sandbox firm* that takes on a value of one if the firm entered the sandbox, and zero for the set of control firms (selected via coarsened exact matching). Column (1) reports results and shows that sandbox firms are 17.6% less likely to be out of business than comparable firms that were not in the sandbox. As the specification includes industry fixed effects, the significant coefficient estimate suggests that differences in default rates are not explained by differences in industry composition across firms. Including firm controls for age, location and CEO

gender does not alter this conclusion in column (2). While columns (1) and (2) compare the sample of sandbox firms to matched control firms, columns (3) and (4) go one step further and weigh each firm by its respective CEM weights to ensure balancedness in co-variates. While the difference in default rates slightly narrows, sandbox firms are still significantly less likely to go out of business (by 14.2% in column 4).

Are sandbox firms also more likely to innovate? To answer this question, we look at the effect of sandbox entry on patenting activity. While patents are a slow moving and infrequent measure of innovation, in the absence of systematic data on customer bases or product launches, they offer a first glimpse into the innovative potential of sandbox firms. The average probability for a firm in our sample to have a patent granted in a given quarter is 1.8%. For sandbox firms, the unconditional average probability is 0.8% before and 1.64% after sandbox entry.

Panel (b) of [Table 4](#) shows that sandbox firms are significantly more likely to have a patent granted post sandbox-entry. We begin by estimating variants of Equation (1) on the within-sandbox sample of firms. The dependent variable is a dummy that takes on a value of one if a firm had a patent granted in a given quarter, and zero otherwise as dependent variable. Column (1), with firm fixed effects, shows that sandbox firms are significantly more likely to be granted a patent post entry. Adding firm-level controls and time fixed effects in columns (2) and (3) does not change this conclusion, although the coefficient declines in significance to the 10% level in column (3). In terms of magnitude, the probability increases by 1.6%. In columns (4)–(6) we perform identical exercises, but compare sandbox firms to the matched sample of control firms. All regressions are weighted by CEM weights. Entry into the sandbox is associated with a significant increase in the probability of having a patent granted. Relative to comparable firms outside the sandbox, the probability increases by 1.9% in column (6).¹⁷

[Figure 2](#), panel (b) investigates whether firms entering the sandbox in earlier cohorts had systematically different patenting activity prior to entry than later entrants. Estim-

¹⁷Logistic regressions show that the probability of having a patent increases by 63% (relative to the average probability) among the sample of sandbox firms, and by 64% when we compare sandbox firms to matched non-sandbox firms. Both coefficient estimates are significant at the 5% level (unreported).

ing Equation (2) with the patent granted dummy as dependent variable, the coefficient plot with corresponding 90% confidence intervals shows that patenting activity is significantly higher after entry, but not before. This suggests that firms that enter the sandbox in quarter t did not patent more before entry than firms that entered the sandbox in later cohorts.

Sandbox firms are not only more likely to survive and patent, but already offer a diverse range of products and services in various areas, including in banking, payment services, regtech, cyber security, insurtech, or asset management. For example, Money Dashboard offers a personal finance management application used by over 500,000 customers. The app collates information from users' bank accounts across UK banks. By automatically organizing the spending data and providing budgeting advice and forecasting analysis, it aims to help improve financial decision making. Another company, Nimba, provides invoice insurance to small and medium enterprises. It now partners with Barclays and Starling Bank. London & Country Mortgages Ltd is a mortgage broker that provides mortgage advice and offers online mortgage applications to multiple lenders that can be tracked 24/7. According to its website, over two million people have used their services. Other companies leverage blockchain technology: Nuggets reportedly provides around 3.5 million web3 users with a decentralized digital ID. Capexmove provides a platform to facilitate the issuance of tokenized debt instruments, with the goal to use blockchain technology to provide greater transparency and speed at a lower cost. The Online Appendix provides further details on the products and services offered by sandbox firms.

4.3 Information Asymmetries and Regulatory Costs

We now examine the channels through which the sandbox affects firms' access to capital. A regulatory sandbox could reduce asymmetric information and the associated information collection costs: it provides reassurance to investors that firms are closely monitored and advised, as well as informed about the regulatory framework. Also, investors may perceive selection into the sandbox as a stamp of honor, a guarantee from the regulator

that the firm is viable and innovative, as these are the criteria by which they are selected. Further, a dedicated case officer that helps to navigate the legal environment could reduce firms' costs to understand and comply with the regulatory framework, thereby reducing regulatory costs.

Information asymmetries in the form of adverse selection and moral hazard are particularly acute for young and small firms (Petersen and Rajan, 1994; Czarnitzki and Hottenrott, 2011), firms that often have no prior track records and are informationally opaque. Identifying viable firms is even more difficult in an uncertain and dynamic environment (Gompers, 1995; Bolton and Freixas, 2000). Fintechs offer novel products and services in an environment of high uncertainty, so we expect informational frictions to be acute – especially among younger and smaller entrants.

Further, a large literature shows that a closer relationship or shorter physical distance between investors and firms reduces informational frictions (Grinblatt and Keloharju, 2001; Degryse and Ongena, 2005).¹⁸ Informational asymmetries are thus expected to be greater for first-time investors (i.e., investors that have not invested into a firm previously), and for investors that are based outside of the UK, since they have an informational disadvantage when investing into UK firms. To investigate these hypotheses, in what follows we perform analyses at the firm and investor-firm level.

Firm-level analysis. Columns (1)–(4) in Table 5 investigate the differential effect of sandbox entry on young and small firms. Columns (1)–(2) report results for our baseline Equation (1), but interact dummy *post SB entry* with a dummy *old firm*, which takes a value of one if a firm's age is above the median (if it is at least four years old).¹⁹ Column (1) uses firm and year fixed effects, column (2) adds industry*time fixed effects. Across specifications, entry into the sandbox is associated with an increase in capital raised for young firms (*old* = 0). Yet, the positive effect is largely offset for old firms, as can be seen from the negative and economically large coefficient on *old*.

Columns (3)–(4) repeat the exercise, but interact dummy *post SB entry* with a dummy

¹⁸For example, investors tend to invest a larger fraction of their portfolio in stocks of geographically close firms (Coval and Moskowitz, 1999) and earn abnormal returns on stocks of firms that are geographically close (Ivković and Weisbenner, 2005).

¹⁹Average age equals 3.2 years in the 'young' group and 13.9 years in the 'old' group.

large firm, which takes a value of one if a firm is affiliated with listed companies, i.e., the firms we initially excluded from our baseline sample. Across specifications, entry into the sandbox is followed by more capital raised by small, but not by large firms. If anything, large firms raise less capital after entering the sandbox.²⁰

To shed further light on the role of informational frictions, we compare venture capital deals to other types of deals in columns (5)–(6). Due to their early-stage nature, venture capital deals entail more uncertainty and information barriers, and thus potentially require more active screening on the part of the investor (Howell, 2020). We therefore expect the estimated effects of entry into the sandbox to be stronger for venture capital deals than for other deals. In column (5) we introduce dummy *VC*, which takes on a value of one if a deal is classified as venture capital deal, and zero otherwise. The effect of sandbox entry on capital raised is economically larger and statistically significant for venture capital deals (for which the effect is about twice as large, compared to other deals), further corroborating our results that the sandbox reduces informational asymmetries. Results are similar when we additionally include time-varying effects at the industry level in column (6).

These stronger effects on venture capital deals could also have implications for growth. Venture capital-backing has been shown to be a good predictor of future firm performance, because start-ups with more promising growth and innovation prospects tend to be funded by VC (Puri and Zarutskie, 2012). Likewise, Akcigit et al. (2022) find that VC funding is concentrated in start-ups that have a patent and with relatively high-quality early innovation. Further contributing to the success of VC-backed companies is the fact that VC investors facilitate access to debt finance, and provide non-monetary resources like management advice, product expertise, and mentoring (Hochberg et al., 2018). We perform additional tests on the effects of sandbox entry on VC deals in Section 5.

We also provide indirect evidence that sandboxes reduce regulatory costs. Anecdotal evidence suggests that firms with a founder with a background in law benefit less from

²⁰This finding can be explained by the fact that two sandbox firms affiliated with large listed companies raised large amounts of funding prior to entry.

the sandbox, because the case officer’s legal advice is less necessary (Deloitte, 2019).²¹ To test this proposition more formally, we introduce an interaction term between *post SB entry* and a dummy *law* into Equation (1). Columns (7)–(8) provide results. Column (7) uses firm and year fixed effects, column (8) adds industry*time fixed effects. Across all specifications, entry into the sandbox leads to an increase in capital raised for firms without a ‘law-degree’ CEO (*law degree* = 0), while the positive effect is around half as large for firms with a CEO that has a background in law or the financial sector.

Foreign and first-time investors. Firm-level results suggest that the sandbox facilitates firms’ access to capital by reducing information asymmetries. We now shed further light on the information channel by investigating the effect of sandbox entry on capital raised from foreign and first-time investors. Granular investor-firm data allow us to address the challenge that our firm-level results could be biased by confounding factors at the investor or firm level. To this end, we estimate variants of the following regression at the firm-investor-quarter level:

$$\begin{aligned} \log(1 + amt)_{i,f,t} = & \delta_1 \textit{post SB entry}_{f,t} + \delta_2 \textit{investor type}_i \\ & + \delta_3 \textit{post SB entry}_{f,t} \times \textit{investor type}_i + \theta_{i,f} + \tau_{f,t} + \nu_{i,f,t}. \end{aligned} \tag{3}$$

The dependent variable is the amount invested by investor *i* in firm *f* in quarter *t*, split on a pro-rata basis. In robustness tests we also split deal volume by investors size. The dummy *post SB entry* takes a value of one after sandbox entry, and zero for all quarters prior to entry. We include the vector of time-invariant firm characteristics interacted with dummy *post SB entry* as controls. Standard errors are clustered at the firm level. To test whether the sandbox alleviates informational frictions, we interact *post SB entry* with the dummies *foreign investor* or *new investor*, denoted by *investor type_i* in regression Equation (3), that take on a value of one if an investor is based outside the UK or has not invested into the firm prior to its entry into the sandbox. As informational frictions are more severe for new or foreign investors, we expect entry into the sandbox to lead to a larger increase in capital raised from these investors, so $\delta_3 > 0$.

²¹The management literature has established that CEO or founder experience and skill is correlated with firm performance (Bhagat et al., 2010; Gottesman and Morey, 2010; Bernstein et al., 2017).

Coefficients in regression Equation (3) could be biased if entry into the sandbox is correlated with confounding investor or firm factors. For example, within the group of firms that enters the sandbox, the exact entry date could be correlated with unobservable firm characteristics. While results in Table 2 and Table 3 suggest that entry into the sandbox is not systematically correlated with firm observables or time-varying factors at the industry*time level, firm-level regression cannot fully account for unobservable firm characteristics that vary over time.

We address this challenge through the inclusion of fixed effects. First, to control for unobservable firm-investor factors, we include investor*firm fixed effects ($\theta_{i,f}$). These fixed effects absorb any time-invariant firm and investor characteristics such as the (informational) distance between the firm and the investor. Second, we can control for unobservable time-varying factors at the firm level through firm*time fixed effects ($\tau_{f,t}$). These fixed effects absorb, for example, changes in firm sales, management, or product quality. That is, we investigate the differential effect of entry into the sandbox on foreign or new investors, holding time-varying unobservable firm fundamentals constant (Khwaja and Mian, 2008; Jiménez et al., 2014).

Table 6 shows that entry into the sandbox is followed by an increase in capital raised also at the investor-firm level. Column (1) includes investor*firm and year fixed effects and shows that entry into the sandbox is associated with an increase in capital raised of 2.7% from the average investor. In columns (2)–(5) we investigate whether the effect of sandbox entry on capital raised depends on investor characteristics related to informational frictions, based on Equation (3).²² Column (2) shows that entry into the sandbox is associated with an increase in capital raised of 3.2% for domestic investors, and 4.3% for foreign investors. Both coefficients are significant at the 5% level. The interaction specification allows us to address the identification challenge that even among the group of firms that enter the sandbox at some point, the date of entry could be correlated with unobservable firm characteristics. Column (3) thus includes time-varying fixed effects at

²²For consistency, we restrict the sample to firms connected to at least two investors and investors connected to at least two firms in each quarter. Estimated coefficients in columns (2) and (4) are similar for the full sample.

the firm level that control for any observable and unobservable confounding factors at the firm level. Results show that firms raise significantly more capital from foreign investors even after we account for time-varying firm characteristics. Including firm*time fixed in our regressions leads to no material change in the estimated coefficients, while the R^2 increases by over 30 percentage points. Unobservable firm characteristics that could be correlated with a firms' entry date are hence unlikely to explain our finding, reducing potential concerns about self-selection and omitted variable bias (Altonji et al., 2005; Oster, 2019).

Columns (4) and (5) report a near-identical picture for new investors. Entry into the sandbox is followed by an increase in capital raised of 2.5% from 'old' and of 4.1% from new investors when we employ investor*firm and year fixed effects. The estimated coefficients are highly significant statistically and economically. Column (5) confirms that firms also raise more capital from new investors after entry into the sandbox when we include firm*time fixed effects. The coefficient on the interaction term remains identical in magnitude and significant at the 1% level.

In conclusion, Table 6 provides support for the hypothesis that the regulatory sandbox reduces informational asymmetries. Firms that enter the sandbox raise more capital from investors based outside the UK and investors that have not previously invested into the firm.

5. Additional Tests

As discussed above VC-backing can signal strong future performance. We therefore consider VC-backing as an alternative indicator of firm quality or success and investigate to what extent entry into the sandbox helps firms to attract VC funding. The results of our analysis of the effect of participating in the sandbox on VC-backing are reported in panel (a) of Table 7. As before we report results for the sample of firms within the sandbox, as well as for the sample of matched control firms. To provide an adequate comparison, we restrict the analysis to VC deals, as well as other types of early-stage deals (including seed capital and capital from angel-individual investors). Across the different specifications,

we find that entry in the sandbox is followed by greater VC funding of 7.4% and 9.4% among firms within the sandbox and when compared to control firms (columns 1 and 2). Columns (3) and (4) use logistic regressions and show that the probability of a firm being backed by VC investors, as opposed to obtaining other types of early-stage capital, is around 1 per cent higher after entry (an around one-third increase in the unconditional probability of a firm raising VC capital).

Column (5) restricts the sample to the eight quarters prior and 12 quarters after sandbox entry. The coefficient on sandbox entry remains statistically significant and large in magnitude, confirming the visual impression in [Figure 1](#): the main effect of sandbox entry on capital raised materializes in the first two years upon entry into the sandbox.²³

Due to the nature of our data, our dependent variable takes on a value of zero in several quarters. We thus estimate our baseline specification using non-linear models that account for the mass of zeros for firms that do not raise capital. Using absolute deal volume as dependent variable in column (6), we estimate a negative binomial regression. In column (7), we estimate a Tobit random effects regression with log deal amount as dependent variable and report average marginal effects with robust standard errors. Results show that entry into the sandbox has a positive and significant effect on total capital raised by fintechs under negative binomial and Tobit regressions as well. The magnitude of the effect is similar to our baseline regressions. In unreported regression, we also confirm that our results hold when we use an inverse hyperbolic sine transformation of deal amounts.

Finally, columns (8)–(9) account for the fact that unobservable factors could affect firms in the same cohort through cohort fixed effects. Confirming our previous results (the absence of pre-trends and the fact that *among* the group of firms that enter the

²³In principle, the market could learn about firms’ quality over time as this quality is gradually revealed to the public. This revelation could have happened irrespective of entry into the sandbox, leading to a steady increase in firms’ ability to raise funding – this effect might be subsumed in our post dummy. Instead, if investors learn about the quality of a firm because of the “sandbox certification”, firms’ ability to raise funding should increase immediately upon entry. Unreported results show that the strongest effects occur in the first two quarters upon entry, suggesting that the increase in funding raised does not reflect a gradual revelation of firms’ quality.

sandbox, the exact entry date is not systematically correlated with firm characteristics), cohort fixed effects do not affect our estimated coefficient in a statistically or economically meaningful way. In column (9) we add contiguous-cohort fixed effects. Potentially, whether a firm participates before or after six months (ie among two contiguous cohorts) is more ‘random’ than before or after eg three years. Yet, results show that baseline results remain almost unaffected.

Panel (b) shows that our results are robust to the use of alternative matching estimators. Based on the full sample of sandbox and control firms, columns (1), (3), and (5) use nearest neighbor (NN) matching, and columns (2), (4), and (6) use propensity score (PS) matching. All columns match on firm age, firm location, and CEO gender. Irrespective of the chosen matching method, the number of nearest neighbors is three. Results show an economically and statistically significant positive effect of entry into the sandbox on capital raised in columns (1)–(2), a negative effect on failure in columns (3)–(4), and a positive effect on patenting in columns (5)–(6).²⁴ Panel (c) reports regressions similar to panel (a), columns (5)–(9), but with the patent dummy as outcome variable. We restrict the sample to the eight quarters prior and 12 quarters after sandbox entry; estimate a negative binomial regression and Tobit random effects regression, and control for cohort and contiguous-cohort fixed effects. Across specifications, sandbox entry is followed by significantly higher patenting activity.

In a final exercise we return to the investor-firm level analysis. First, we look at alternative outcome variables. The investor-level analysis in [Table 6](#) assumes a pro-rata split of deal volume across investors. In [Table 8](#) we relax this assumption. Panel (a) splits deal volume by investors ‘size’, measured by their total investments. For example, if the deal size is \$100 and there are two investors, one with aggregate investments of \$1500 and one with aggregate investments of \$500, we assign \$75 to the first and \$25 to the second investor. Panel (b) uses the dummy *capital raised* as dependent variable, which takes on a value of one if a given investor invests in a given firm in quarter t (the extensive margin), and zero otherwise. This approach is hence insensitive to the chosen

²⁴We obtain similar effects when we match on one nearest neighbor or additionally match on firm industry (unreported).

method of allocation. In addition, we investigate whether changes in investors' overall supply of capital could coincide with the time when firms enter the sandbox by including investor*time fixed effects in Equation (1). For example, a change in the tax regime that reduces capital taxes on investments in fintechs could relax investors' constraints.

Columns (1) and (2) in panels (a) and (b) show that controlling for confounding time-varying factors at the investor level through investor*time fixed leads to an increase in the magnitude of the estimated coefficient. Were our findings driven by a higher supply of capital by investors that invest in sandbox and non-sandbox firms, we would find no effect of sandbox entry on capital raised by sandbox firms *after* accounting for changes in the supply of capital across all firms of an investor. Further, columns (3)–(6) in both panels show that our main findings remain unaltered for alternative constructions of the outcome variables: entry into the sandbox is followed by a significant increase in capital raised, especially among foreign and new investors. These findings are unaffected by the inclusion of time-varying fixed effects at the firm level.

6. Conclusion

Our paper contributes to the current debate on public policy to foster innovation (OECD, 2017). Policy makers face the challenge of promoting innovation in the financial sector without compromising data privacy, financial stability or consumer welfare. To meet this objective, over 50 jurisdictions have already set up a regulatory sandbox (World Bank, 2020). By fostering innovation in a controlled environment, regulators hope to learn about new technologies and the associated risks before they see rapid adoption by consumers. Despite the wide-spread introduction of sandboxes, to the best of our knowledge we provide the first systematic analysis of their effectiveness in helping fintechs raise capital and the underlying channels.

Our findings suggest that firms entering the UK regulatory sandbox raise significantly more capital in the quarters after entry. They are also more likely to be still in operation and have patents. We thereby provide supportive evidence that sandboxes achieve one of their key goals: to help young fintechs raise capital and spur innovative activity. This

finding suggests that sandboxes could become a successful policy tool for harnessing the benefits of financial innovation. However, the caveat that sandbox entry is not random should be kept in mind when interpreting our results.

Our results do not necessarily imply that sandboxes are unambiguously welfare-enhancing. Operating sandboxes often requires public funds, and helping young firms raise capital is only one objective besides others, for example increasing consumer welfare or maintaining financial stability. While the short time span since their inception does not allow for an evaluation of the effects of regulatory sandboxes on consumer surplus or financial stability, this paper provides a first step toward understanding how regulatory collaboration with fintechs affects their ability to raise capital and attendant real effects. Our positive findings can be seen as an encouragement for policymakers to scale up experimentation in sandboxes and share the lessons learned by means of regular publications and guidelines based on their experience.

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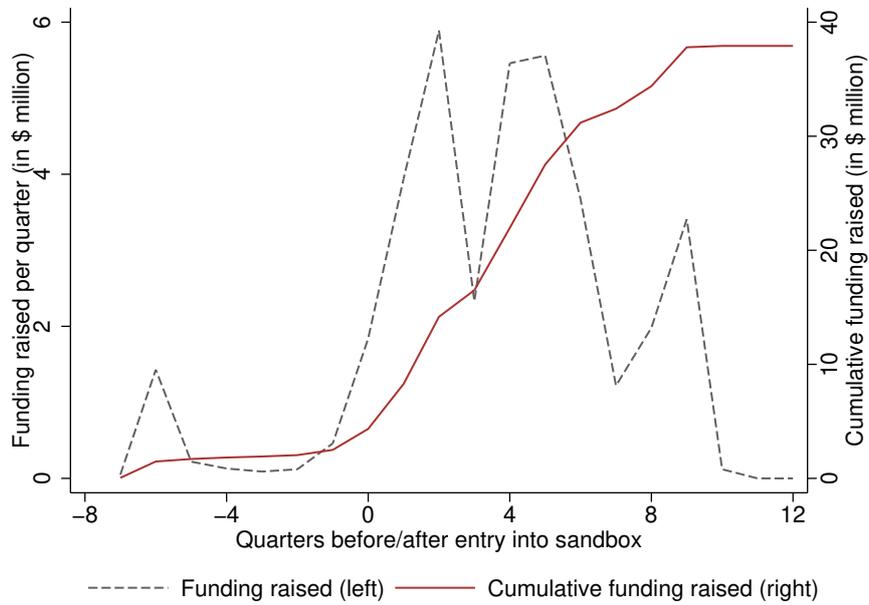
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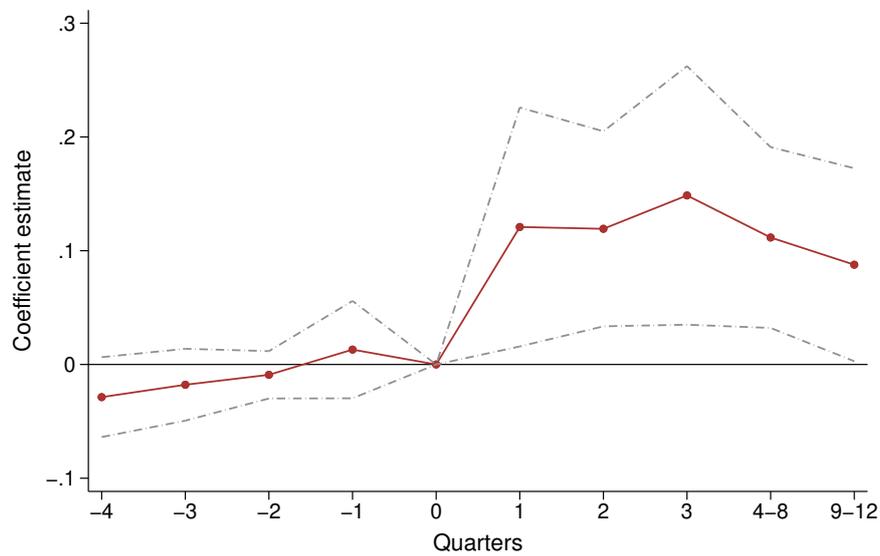
Figures and Tables

Figure 1: Funding raised by sandbox firms

(a) Deal volume around sandbox entry date



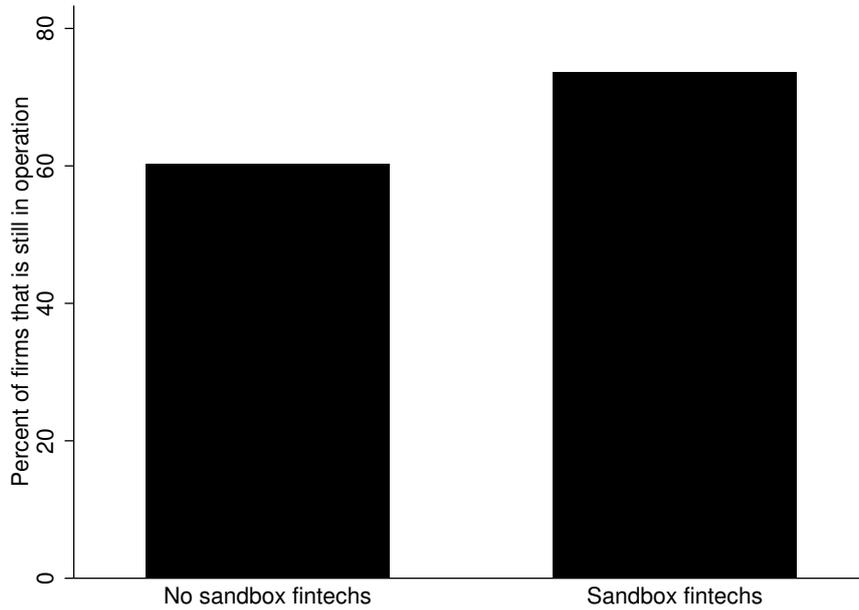
(b) Coefficient plot: pre-trends



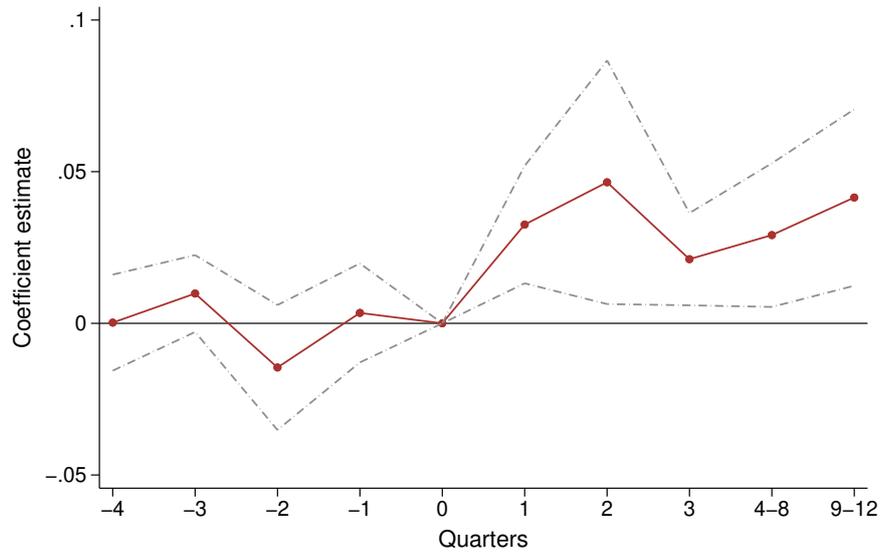
Note: Panel (a) plots total quarterly funding raised (left axis) and cumulative funding raised (right axis, both in \$mn) by our sample of sandbox fintech firms. Negative values on the horizontal axis denote the quarters before sandbox entry, zero the quarter of entry, and positive values the quarters post-sandbox entry. Panel (b) shows coefficient estimates of β_k from Equation (2). Value zero on the horizontal axis corresponds to the date of entry, and β_k is the estimated change in deal amount t quarters before or after entry. Dashed lines represent 90% confidence intervals.

Figure 2: Survival and patenting

(a) Sandbox fintechs are more likely to survive



(b) Coefficient plot: pre-trends in patenting



Note: Panel (a) plots the average share of firms that are still in operation (as of 2022q1) among the group of fintechs that entered the sandbox during the sample period ('Sandbox fintechs'), as well as among the matched set of control firms that did not enter the sandbox ('No sandbox fintechs'). Observations are weighted by the respective CEM weights. Panel (b) shows coefficient estimates of β_k from Equation (2), but with the dummy *patent granted* as dependent variable. Value zero on the horizontal axis corresponds to the date of entry, and β_k is the estimated change in the likelihood to patent t quarters before or after entry. Dashed lines represent 90% confidence intervals.

Table 1: **Descriptive statistics**

(a): Firm characteristics

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
Deal amount (USD mn)	908	4.683	27.495	0	387	0	0	0
Log(deal amount)	908	.029	.154	0	1.583	0	0	0
Capital raised (dummy)	908	.061	.239	0	1	0	0	0
Patents	862	.018	.107	0	1	0	0	0
Failed	198	.363	.482	0	1	0	0	1

(b): Age, location, and CEOs

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
Age (as of 2019)	56	6.464	10.105	0	58	3	4	5
Log(company age)	56	1.663	.7	0	4.078	1.386	1.609	1.792
Firm based in London	56	.518	.504	0	1	0	1	1
CEO is male	56	.804	.401	0	1	1	1	1
Nr. of CEOs	56	1.107	.366	1	3	1	1	1

Note: Panels (a) provides summary statistics for the main variables at the firm-quarter level for the sample of sandbox firms, as well as the failure rate for sandbox and controls firms. Panel (b) shows summary statistics for firm-level variables for sandbox firms.

Table 2: **Firm characteristics and sandbox cohort**

VARIABLES	(1) Age	(2) London	(3) Revenue	(4) CEO male	(5) Nr. of CEOs	(6) Firm FE
Sandbox cohort 2	-3.448 (3.872)	0.097 (0.207)	0.260 (0.202)	0.221 (0.181)	0.052 (0.170)	0.028 (0.018)
Sandbox cohort 3	-4.716 (3.817)	-0.045 (0.243)	0.295 (0.225)	0.364** (0.152)	0.034 (0.153)	0.015 (0.019)
Sandbox cohort 4	-3.424 (3.964)	0.055 (0.206)	0.079 (0.207)	0.164 (0.187)	0.042 (0.129)	-0.002 (0.014)
Sandbox cohort 5	5.784 (8.136)	-0.420** (0.199)	-0.080 (0.239)	0.114 (0.221)	-0.091 (0.091)	-0.007 (0.014)
Observations	56	56	56	56	56	56
R-squared	0.114	0.112	0.074	0.077	0.017	0.125

Note: This table reports results for firm-level regressions with different firm characteristics as outcome variables. As explanatory variable, we include dummies for each cohort, where *sandbox cohort 1* is the reference group. The outcome variables (from left to right) are firm age, a dummy with a value of one if a firm is located in London, a dummy with value one if a firm reports that it is already generating revenue, a dummy with a value of one if the CEO is male, and the number of CEOs. Column (6) uses the firm fixed effects, resulting from a regression of log deal amount on firm fixed effects, as dependent variable. Standard errors are robust. *** p<0.01, ** p<0.05, * p<0.1

Table 3: **Entry into the sandbox and capital raised**

(a): Sandbox sample

VARIABLES	(1) Log(deal amt)	(2) Log(deal amt)	(3) Log(deal amt)	(4) Log(deal amt)	(5) Capital raised	(6) Capital raised
Post SB entry	0.093* (0.054)	0.137** (0.056)	0.148** (0.064)	0.150** (0.070)	0.031* (0.017)	0.031** (0.014)
Observations	908	908	908	855	908	908
R-squared	0.016	0.076	0.093	0.157		
Firm FE	-	✓	✓	✓	-	✓
Time FE	-	-	✓	-	-	✓
Industry*Time FE	-	-	-	✓	-	-

(b): Matched control firms

VARIABLES	(1) Log(deal amt)	(2) Log(deal amt)	(3) Log(deal amt)	(4) Log(deal amt)	(5) Capital raised	(6) Capital raised
Post SB entry	0.107** (0.053)	0.121** (0.054)	0.120** (0.056)	0.151** (0.055)	0.026*** (0.009)	0.033*** (0.008)
Observations	3,779	3,779	3,779	3,779	3,779	3,779
R-squared	0.025	0.091	0.104	0.133		
Firm FE	-	✓	✓	✓	-	✓
Time FE	-	-	✓	-	-	✓
Industry*Time FE	-	-	-	✓	-	-

Note: Panel (a) presents results from firm-quarter level regression Equation (1), based on the sample of firms that entered the sandbox at some point during our sample. The dependent variable is either the logarithm of 1 plus the total deal amount for firm f in quarter t in columns (1)–(4); or the dummy *capital raised* that takes on a value of one if the firm raises a positive amount of capital in a given quarter in columns (5)–(6). *Post SB entry* is a dummy with a value of one after sandbox entry, and zero for all quarters prior to entry. All regressions include time-invariant firm characteristics log age, CEO gender, and London dummy, interacted with *Post SB entry*, as controls. Standard errors are clustered at the firm level. Columns (5)–(6) report average marginal effects from logistic regressions with robust standard errors. Panel (b) performs identical regressions, but uses the sample of sandbox firms and the sample of control firms, employing coarsened exact matching. *** p<0.01, ** p<0.05, * p<0.1

Table 4: **Real effects**

(a): Survival rates

	(1)	(2)	(3)	(4)
VARIABLES	Failed	Failed	Failed	Failed
Sandbox firm	-0.176** (0.083)	-0.173** (0.082)	-0.141* (0.084)	-0.142** (0.073)
Observations	198	198	198	198
Controls	-	✓	-	✓
Industry FE	✓	✓	✓	✓

(b): Patents

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Patent	Patent	Patent	Patent	Patent	Patent
Post SB entry	0.018** (0.007)	0.019** (0.007)	0.016* (0.008)	0.017*** (0.007)	0.019*** (0.007)	0.019** (0.008)
Observations	862	862	862	3,741	3,741	3,741
R-squared	0.388	0.389	0.407	0.417	0.419	0.421
Firm FE	✓	✓	✓	✓	✓	✓
Controls	-	✓	✓	-	✓	✓
Time FE	-	-	✓	-	-	✓

Note: Panel (a) presents results from logistic regressions at the firm-level, based on the sample of sandbox firms and the sample of matched control firms. The dependent variable is a dummy with a value of one if a firm failed, and zero otherwise. All regressions include industry dummies. Time-invariant firm characteristics firm age, CEO gender, and a London dummy are included as controls. Columns (3) and (4) weight regressions by the respective CEM weights. All columns report average marginal effects from logistic regressions with robust standard errors. Panel (b) reports results from regressions at the firm-quarter level, based on the sample of sandbox firms and the sample of matched control firms. The dependent variable is a dummy with a value of one if a firm had a patent granted in a given quarter, and zero otherwise. Time-invariant firm characteristics log age, CEO gender, and the London dummy, interacted with *Post SB entry*, are included as controls. Columns (1)–(3) focus on the sample of within-sandbox firms. Columns (4)–(6) add the sample of matched control firms and weight regressions by the respective CEM weights. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Information asymmetry and CEO background

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(deal amt)	Log(deal amt)	Log(deal amt)	Log(deal amt)	Log(deal amt)	Log(deal amt)	Log(deal amt)	Log(deal amt)
Post SB entry	0.106** (0.043)	0.109** (0.046)	0.229** (0.092)	0.101* (0.054)			0.193*** (0.072)	0.215*** (0.075)
Post SB entry × old firm	-0.072** (0.031)	-0.064* (0.034)						
Post SB entry × large firm			-1.832*** (0.582)	-0.906*** (0.054)				
Venture capital					0.178*** (0.054)	0.182** (0.086)		
Post SB entry × venture capital					0.191** (0.094)	0.187** (0.097)		
Post SB entry × law degree							-0.103* (0.058)	-0.121* (0.065)
Observations	908	855	995	931	908	855	908	855
R-squared	0.098	0.161	0.239	0.383	0.390	0.450	0.095	0.160
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	-	✓	-	✓	-	✓	-
Industry*Time FE	-	✓	-	✓	-	✓	-	✓

Note: This table presents results from firm-quarter level regressions (see Equation (1)), based on the sample of firms that entered the sandbox at some point during our sample. The dependent variable is the logarithm of 1 plus the total deal amount for firm f in quarter t . *Post SB entry* is a dummy with a value of one after sandbox entry, and zero for all quarters prior to entry. All regressions include time-invariant firm characteristics log age, CEO gender, and London dummy, interacted with *Post SB entry*, as controls. *old firm* is a dummy with a value of one for firms above the median in terms of firm age; *large firm* is a dummy with a value of one for firms associated with large or listed firms; *venture capital* is a dummy with a value of one if a deal is classified as a VC deal; and *law degree* is a dummy with a value of one for firms that have a CEO with a law degree. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: **Accounting for investor and firm characteristics**

VARIABLES	(1) Log(deal amt)	(2) Log(deal amt)	(3) Log(deal amt)	(4) Log(deal amt)	(5) Log(deal amt)
Post SB entry	0.027** (0.011)	0.032** (0.020)		0.025** (0.012)	
Post SB entry \times foreign investor		0.011** (0.005)	0.012*** (0.004)		
Post SB entry \times new investor				0.016*** (0.006)	0.016*** (0.005)
Observations	41,745	34,249	34,249	34,249	34,249
R-squared	0.031	0.032	0.354	0.032	0.353
Investor*Firm FE	✓	✓	✓	✓	✓
Time FE	✓	✓	-	✓	-
Firm*Time FE	-	-	✓	-	✓

Note: This table presents results from firm-investor-quarter level regressions (see Equation (3)), based on the sample of firms that entered the sandbox at some point during our sample. The dependent variable is the logarithm of 1 plus total capital invested by each investor, based on a pro-rata split. *Post SB entry* is a dummy with a value of one after sandbox entry, and zero for all quarters prior to entry. *foreign investor* and *new investor* are dummies that take on a value of one if the investor is not headquartered in the UK or has not invested into the firm prior to its entry into the sandbox. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: **Further robustness tests**

(a): VC funding and alternative specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Log(VC deal amt)	weighted Log(VC deal amt)	Has VC deal	weighted Has VC deal	-8 to +12 Log(deal amt)	neg bin Deal amt	Tobit Ddeal amt	cohort FE Log(deal amt)	cont cohort FE Log(deal amt)
Post SB entry	0.074* (0.044)	0.094** (0.047)	0.009 (0.006)	0.011** (0.066)	0.138** (0.066)	0.113** (0.053)	0.149* (0.088)	0.148** (0.064)	0.145** (0.063)
Observations	707	2,740	707	2,740	762	908	908	908	908
R-squared	0.077	0.084			0.127			0.093	0.096
Firm FE	✓	✓	✓	✓	✓	-	-	✓	✓
Time FE	✓	✓	✓	✓	✓	-	-	✓	✓

(b): Nearest neighbor and propensity score matching

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	NN(3) Capital raised	PS(3) Capital raised	NN(3) Failed	PS(3) Failed	NN(3) Patent	PS(3) Patent
Post SB entry	0.027*** (0.008)	0.064** (0.021)			0.017** (0.008)	0.016** (0.008)
Sandbox firm			-0.125** (0.079)	-0.132** (0.080)		
Observations	3,779	3,779	198	198	3,741	3,741

(c): Real effects – alternative specifications

	(1)	(2)	(3)	(4)	(5)
VARIABLES	-8 to +12 Patents	neg bin Patents	Tobit Patents	cohort FE Patents	cont cohort FE Patents
Post SB entry	0.018** (0.008)	0.015* (0.008)	0.014* (0.008)	0.017** (0.008)	0.016* (0.009)
Observations	737	862	862	862	862
R-squared	0.407			0.407	0.407
Firm FE	✓	-	-	✓	✓
Time FE	✓	-	-	✓	✓

Note: Panel (a) presents results from firm-quarter level regressions (see Equation (1)). The dependent variable is the logarithm of 1 plus the total VC deal amount for firm f in quarter t in columns (1)–(2) and a dummy with value one if a firm had any VC deal in a given quarter in columns (3)–(4). The dependent variable is the logarithm of 1 plus the total deal amount for in columns (5), (8), and (9). It is the total deal amount in columns (6) and (7). Columns (5) narrows the time window around the entry date into the sandbox. Columns (6) and (7) estimate negative binomial and Tobit regressions and report average marginal effects with robust standard errors. Column (8) employs fixed effects for each individual cohorts level, column (9) uses fixed effects for contiguous cohorts. *Post SB entry* is a dummy with value one after sandbox entry, and zero for all quarters prior to entry; *Sandbox firm* is a dummy with value one if a firm is in the sandbox. All regressions include time-invariant firm characteristics log age, CEO gender, and London dummy, interacted with *Post SB entry*. Panel (b) uses the sample of sandbox firms and the sample of control firms and uses nearest neighbor and propensity score matching, based on the three nearest neighbors. The dependent variable is the logarithm of 1 plus the total deal amount for firm f in quarter t in columns (1)–(2), whether firm f has failed in columns (3)–(4), and whether it has a patent in quarter t in columns (5)–(6). In panel (c), the dependent variable is a dummy with a value of one if a firm had a patent granted in a given quarter, and zero otherwise. It replicates the specifications in columns (5)–(9) in panel (a). Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: **Investor-firm analysis – alternative outcome variables**

(a): Total capital invested

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	by size Log(deal amt)					
Post SB entry	0.040*** (0.014)	0.062** (0.027)	0.041** (0.026)		0.040** (0.027)	
Post SB entry × foreign investor			0.025** (0.010)	0.027** (0.011)		
Post SB entry × new investor					0.028** (0.009)	0.028** (0.010)
Observations	41,745	41,717	34,249	34,249	34,249	34,249
R-squared	0.033	0.236	0.236	0.561	0.237	0.562
Investor*Firm FE	✓	✓	✓	✓	✓	✓
Time FE	✓	-	-	-	-	-
Investor*Time FE	-	✓	✓	✓	✓	✓
Firm*Time FE	-	-	-	✓	-	✓

(b): Any capital invested

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	dummy Capital raised					
Post SB entry	0.104* (0.061)	0.161** (0.053)	0.155** (0.056)		0.159** (0.051)	
Post SB entry × foreign investor			0.082** (0.034)	0.090*** (0.027)		
Post SB entry × new investor					0.107** (0.012)	0.105** (0.012)
Observations	41,745	41,717	34,249	34,249	34,249	34,249
R-squared	0.024	0.263	0.263	0.616	0.262	0.616
Investor*Firm FE	✓	✓	✓	✓	✓	✓
Time FE	✓	-	-	-	-	-
Investor*Time FE	-	✓	✓	✓	✓	✓
Firm*Time FE	-	-	-	✓	-	✓

Note: This table presents results from firm-investor-quarter level regression Equation (3), based on the sample of firms that entered the sandbox at some point during our sample. The dependent variable is the logarithm of 1 plus total capital invested by each investor split deal volume by aggregate investors size in panel (a). Panel (b) uses dummy *Capital raised* as dependent variable that takes on a value of one if a given investor invests in a given firm in quarter t (the extensive margin). *Post SB entry* is a dummy with value one after a firm entered the sandbox, and zero for all quarters prior to entry. *foreign investor* and *new investor* are dummies that take on a value of one if the investor is not headquartered in the UK or has not invested into the firm prior to its entry into the sandbox. All regressions include time-invariant firm characteristics log age, CEO gender, and London dummy, interacted with *Post SB entry*, as controls. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Data availability: The data underlying this article were provided by Pitchbook Data by permission. Access to the data can be purchased from Pitchbook Data.

Online Appendix for “Regulatory Sandboxes and Fintech Funding: Evidence from the UK”*

List of Selected Sandbox Companies and Business Description. Note: The information on sandbox firms in our sample is obtained from company websites as of 2023q1, if available.

- AssetVault (www.asset-vault.com): Developer of a digital asset platform designed to record, protect and manage digital assets on the blockchain. The company’s platform helps to catalog different types of the digital assets (eg financial records like equities, debt instruments, and cryptocurrencies) to enable financial institutions to manage insurance policies and claims in one place and get adequate asset protection at a good price.
- Billon (www.billongroup.com): Developer of distributed ledger technology (DLT) protocol and system designed to provide new distributed digital cash and document support. The company’s system is used by banks to issue and redeem digital cash, and using the company’s protocol, banks’ issue keys to legally validate transactions without intervening in the transaction itself. The goal is to enable banks to leverage a legal structure that is identical to pre-paid cards with no regulatory adjustments.
- Blink Innovation (www.blinkblink.io): Developer of a digital flight insurance platform designed to offer real-time flight-disruption insurance. The company’s digital insurance platform utilizes big data and data analytics to track flights and make bookings, providing businesses with high frequency, low severity claims across commercial travel as well as climate, energy, and IoT sectors.
- Capexmove (www.capexmove.io): Developer of DLT-based software solutions designed for issuing tokenized debt. The company’s software lets companies issue programmable debt to create tradable units and thereafter track and settle them at a lower cost than current debt capital markets, with the goal to enable small companies to raise capital in a more efficient and streamlined way.
- Chasing Returns (www.chasingreturns.com): Developer of a trading performance management platform designed to manage clients’ behavior and increase trading success. The company’s trading performance management offers a real-time risk management tool that provides alerts of every stock movement, enabling clients to track their stocks minutely.

* Citation format: Cornelli, Giulio, Sebastian Doerr, Leonardo Gambacorta and Ouarda Merrouche, Internet Appendix to ‘Regulatory Sandboxes and Fintech Funding: Evidence from the UK’, Review of Finance.

- Creditscript (www.creditscript.com): Developer of a financial platform catering to entrepreneurs and businesses. The company's platform helps build and automate financial workflows and offers multi-currency payment accounts, global SWIFT payments, and local payment accounts, enabling clients to automate revenue collection and payments.
- Dashly (www.dashly.com): Developer of a mortgage comparison and switching platform designed to help brokers save money for their clients. The company's platform uses artificial intelligence, big data, and open banking-powered technology to scour the mortgage market, tracking different factors and comparing various lender deals against clients' existing mortgages to identify savings, enabling clients to identify opportunities for them to increase their revenue, taking into account all fees and early repayment charges.
- Etherisc (www.etherisc.com): Operator of an insurance platform intended to facilitate access to reinsurance investments. The company's platform builds decentralized insurance applications, trying to make the purchase and sale of insurance efficient, to offer low operational costs and increase transparency and fairness of insurance, with the goal to provide access to insurance at an affordable price.
- FloodFlash (www.floodflash.co): Developer of a flood insurance technology designed to support people in high-risk areas. The company's technology is a sensor-based product that uses an algorithm to detect the water level before exceeding a critical depth which helps in providing personalized and competitive flood policies, enabling customers to settle flood insurance at affordable rates.
- FutureFlow Research (www.futureflow.org): Provider of cloud computing services designed to map out the movement of funds in the financial system. The company's services offer to manage monetary economics by using its big data and cloud computing systems, enabling central banks, governments, and commercial banks to work together while protecting customer confidentiality.
- Globacap (www.globacap.com): Developer of a digital capital-raising platform intended to automate and significantly streamline post-trade processes. The company focuses on the digitization of assets through blockchain technology to support businesses in their entire capital lifecycle, offering a single, centralized ecosystem that enables creation, management, and transactions of digitized equity, with the goal of enabling frictionless asset creation and transferability.
- Issufy (www.issufy.com): Developer of an AI-enabled platform intended for primary capital markets information management. The company's AI-enabled platform is designed to enable investment banks, brokers, and advisory firms to improve various

aspects of collaboration with asset management clients during complex primary transactions, providing users a solution for better quality feedback and demand information to be gathered, analyzed, and visualized, with full deal documentation management.

- Jamm Today (www.jammtoday.typeform.com): Developer of an online investment platform intended to assist in comparison and review of different investment options. The company's platform provides a custom curated list of digital investment managers based on needs, investment amount and preferred risk level, enabling users to simplify their investment decisions and invest in suitable financial products.
- Laka (www.laka.co): Developer of a peer-to-peer bicycle insurance platform intended to protect bikes. The company's platform pools coverage among a community of like-minded users who are collectively given a competitive price that covers theft, vandalism, damage, and loss as well as provides recovery advice and treatments, with the goal of providing users with a cost-effective and fairer insurance product.
- London & Country Mortgages (www.landc.co.uk): Provider of mortgage services. The company's services include mortgage and remortgage and other brokerage services. Provides mortgage advice and offers online mortgage applications that can be tracked 24/7.
- Money Dashboard (www.moneydashboard.com): Developer of a personal finance management application designed to help users manage their finances. The company's application pulls in bank statement data from accounts across UK banks and then automatically organizes the spending data, providing budgeting advice and forecasting analysis, with the goal of enabling users to make better financial decisions.
- Muinmos (www.muinmos.com): Operator of a cloud-based client onboarding platform intended to allow financial institutions and companies to onboard clients within minutes. The company's platform strives to automatically perform all parts of the onboarding chain, from client categorization, suitability and appropriateness checks where applicable, to know your customer/anti-money laundering checks (identity verification, company data, politically exposed person, sanctions, adverse media, and more), to a comprehensive client risk assessment. It allows institutions to get all onboarding related services from one provider, with the goal of enabling financial institutions to instantly and globally validate whether they can onboard a client in any part of the world.

- Nimbla (www.nimbla.com): Developer of a digital insurance platform designed to protect small and medium-sized businesses against insolvent and late-paying customers. The company's software offers single invoice insurance, predictive cash flow, risk analysis, and trade credit protection, enabling clients to manage their credit exposure, peer ratings, client prospecting tools, and insurance invoices against default, sentiment, and ledger analysis.
- NorthRow (www.northrow.com): Developer of digitized compliance technologies intended for regulated businesses to support the fight against financial crime. The company's platform aims to accelerate onboarding processes and increases the effectiveness of client due diligence by continually monitoring relevant changes in customer profiles to proactively manage regulatory risks, enabling businesses to improve their customers' experiences and meet compliance requirements.
- Nuggets (www.nuggets.life): Developer of an e-commerce payment and ID verification platform designed to store personal and payment data securely on the blockchain. The company's platform provides users with a single biometric tool for login, payment, and identity verification without sharing or storing data, with the goal of avoiding data breaches, and permits consumers to create a secure personal cloud of data in zero-knowledge blockchain storage, with the goal of enabling customers to make payments and use services without worrying about their privacy or security.
- Oval Money (www.ovalmoney.com): Developer of an online financial application designed to provide financial coaching and planning. The company's application provides easy to read, readily available information on everyday expenses, by connecting with any bank account or card, thus aggregating, categorizing and simplifying the information from bank statements, enabling people to gain financial knowledge and encourage savings.
- Pluto (www.visitpluto.com): Provider of information technology outsourcing services intended to help customers to improve business processes and product development. The company's services include product design, web development, digital and e-commerce strategy, and mobile application support services enabling brands to propel themselves through the ever-complicated digital landscape.
- Provable Things (www.provable.xyz): Developer of a blockchain platform intended to create a reliable connection between Ethereum smart contracts and other world wide web applications. The company's platform is used for blockchain applications to overcome common limitations while minimizing additional trust lines, with the goal of enabling clients to decentralize applications to connect with applications in the web.

- Rebank (www.rebanknow.com): Provider of a banking task automation platform intended to solve banking tasks in a timely manner. The company's platform learns about users' banking workflows and provides real-time alerts and task prediction, as well as automates accounts payable with notifications from all accounts, helping clients to automate banking tasks from all across their accounts.
- Saffe (www.saffe.ai): Developer of an AI facial recognition technology designed to facilitate payments and secure authentications. The company's technology aims to eliminate the use of cards and phones to complete transactions by offering a convenient alternative to financial transactions and authentications in general, enabling users to make transactions safer.
- Salary Finance (www.salaryfinance.com): Operator of a financial platform intended to facilitate managing money and help improve the financial situation of clients. The company's platform offers a range of salary-linked employee benefits that help to improve financial well-being, enabling employees around to become financially healthier.
- Sherpa (www.sherpascore.com): Provider of insurance services intended to offer comprehensive services for personal risk management. The company's services include providing tailored life insurance, critical illness insurance, and other sectors of the insurance business and it has also developed a platform that provides insurance-related information, enabling users to find the right insurance plan according to their needs.
- Spherical Defence (www.sphericaldefence.com): Developer of a web firewall application programming interface designed to safeguard the digital infrastructure of banks from cyber-attacks. The company's application programming interface uses deep learning and artificial intelligence technology to detect hacking attempts, perform pen tests on corporate websites and consult them on their cybersecurity, enabling banks to detect hackers trying to access and tamper their systems.
- Square Book (www.squarebook.co.uk): Provider of financial services intended to offer auction technology for equity capital fundraising, and automated ways to IPOs in markets globally. The company's real-time insights provide issuers with a greater level of transparency and reassurance. The goal is to reduce frictions and inefficiencies in the IPO process.
- Twenty Thirty (www.2030.io): Developer of Blockchain technology intended to create a decentralized network. The company develops Blockchain-based technologies which include a cryptocurrency storage and exchange platform, a health wallet,

and a flight delay insurance service, with the goal to help clients to decentralize networks, remove middlemen and accelerate innovation.

- World Reserve Trust (www.worldreservetrust.com): Developer of a financial platform intended to facilitate cheaper and faster global trade payments and settlements. The company's platform uses an asset-linked smart token that utilizes a permission DLT network, with the goal to benefit clients through lower costs and latency, and superior operational characteristics of transitive tokens.
- Wrisk (www.wrisk.co): Developer of a customizable insurance platform designed to empower brands across the industry to build a frictionless, mobile-first insurance experience. The company aims to resolve the insurance implications with mobility trends such as electric and self-driving cars. It also allows customers to manage their insurances seamlessly through a single application.
- Yoti (www.yoti.com): Developer of a digital identity platform designed to provide a simple and secure way of proving identities online and face to face. The company's platform uses artificial intelligence and machine learning algorithms for secure age checking services while saving time and money instantly by sending verified details facilitates secure registration and authentication into websites and offers bank-level data encryption to ensure customers' personal details are stored securely, enabling businesses to store, verify and authenticate the identity of their customers.

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