K Wasn't Built in a Day: Investment with Endogenous Time to Build

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Abstract

We show firms expedite ongoing capital expenditure projects and start fewer projects when credit tightens using project-level data from India and quasi-experimental variation in credit supply. We rationalize our findings with a novel investment model with endogenous time to build. Tighter credit incentivizes firms to accelerate near-completion projects for faster cash flows while delaying early-stage projects, a mechanism borne out in the data. A quantitative macro model disciplined by our estimates shows endogenous time to build generates endogenous amplification and state-dependence along the project maturity distribution. We show novel implications for monetary policy and investment tax credits.

Keywords: Investment, Business Fluctuations, Corporate Finance, Time to Build
JEL classification codes: E20, E22, G31.

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1 Introduction

Capital formation is central to economic fluctuations and long-run growth. A defining feature of physical capital – factories, power plants, bridges, and so on – is time to build. Almost all investment models treat time to build as fixed. This paper challenges this assumption: can firms adjust timelines of ongoing projects when economic conditions change? Should they? Empirically, we leverage project-level data to show that time to build is *endogenous*: firms systematically adjust investment plans and timelines in response to shocks. Theoretically, we introduce a new investment model with endogenous time to build where firms optimally choose the pace of project completion. The framework rationalizes our empirical findings, upends conventional thinking in capital budgeting, and implies state-dependent investment dynamics depending on the distribution of project maturities. We demonstrate how it can (i) attenuate or reverse standard transmission channels of interest rate policy; and (ii) provide insights for the timing of fiscal policy.

Our research question requires us to track investment projects over time. This information is not readily available in accounting records or most data sources used in the extant investment literature. We overcome this measurement challenge by obtaining project-level data on large capital expenditure projects in India. By combining event diaries with extensive data cleaning, we construct a panel tracking projects over time. Another advantage of our data is its cross-sectional richness. In contrast with prior work, we observe public and private projects (e.g., office buildings versus roads) across a wide cross-section of end-user industries (e.g., pharmaceutical versus cement manufacturing plants). We leverage this richness to provide novel facts on time to build, offering new portable moments to investment models while providing context to our identification strategy. We find a median time to completion of 2.5 years, but 5% of projects take over 15 years. Consistent with a role for technological primitives, (i) a 1% increase in project size increases time to build by 0.18%, and (ii) industry accounts for 30% of the cross-sectional variation in completion times.

We provide evidence for an endogenous margin of time to build. Suppose a firm experiences a shock to its economic environment that is plausibly orthogonal to the daily affairs of project construction. Under a null of exogenous time to build, the firm-level shock should not affect project completion. We provide evidence against this view by studying a credit supply shock. For identification, we leverage large-scale bank audits by the Reserve Bank of India, which forced commercial banks to considerably increase loan loss provisions for non-performing assets. The audit led to a contraction in credit supply (Chopra et al., 2020): controlling for demand, banks that had to put up more provisions reduced lending relative to less exposed banks. We then leverage this audit shock as a quasi-experiment to study what firms do to project timelines when credit dries up.

To trace the shock from banks to capex projects, we construct a firm-level exposure vari-

able: firms are more exposed to the bank shock if they borrowed more from exposed banks prior to the shock. Our main finding is that completion hazards increase for projects of more exposed relative to less exposed firms, consistent with *acceleration of ongoing projects*.[1] On the extensive marigin, we also find that more exposed firms *start fewer new projects* following the shock, consistent with standard investment theory. In our preferred specifications, a one-standard deviation increase in firm-level exposure raises the completion hazard by 6% and lowers project starts by 7.5%.

The acceleration result is at odds with exogenous time to build. Though at first surprising, we show it is consistent with a model of investment with endogenous time to build. Our theory further provides a sharper test: following the shock, mature projects should be sped up, whereas fledgling projects should be slowed down. These heterogeneous effects are borne out in the data: completion hazards increase more for projects proxied to be closer to completion; and effects turn negative for early-stage projects.

Our identification strategy relies on the bank-level shocks being exogenous relative to project and firm-level unobservables, conditional on controls. First, previous work supports quasi-randomness of the shock (Chopra et al., 2020). Second, we include a detailed set of fixed effects and firm-level controls to minimize confounding concerns. Third, our credit supply regressions provide evidence against the hypothesis that banks were differentially cutting credit based on unobservable, time-varying firm characteristics. Fourth, panel and cross-sectional balance tests also show that firm-level shock exposures do not correlate with firm-level observables. Fifth, bank shocks are not driven by lending to a small number of bad firms, reducing concerns of shock endogeneity. Last, we provide corroborating anecdotal evidence and a battery of tests to bolster our interpretation of the findings relative to competing stories (i.e., differential censoring or ex post changes in scope). We cannot address threats related to unobserved project quality, a data limitation that qualifies our findings.

To rationalize our empirical findings, we develop an investment model with endogenous time to build. Our setup is minimalist and portable, lending itself to further applications and extensions. In our basic setup, a firm invests in a collection of heterogeneous, irreversible projects. Each project takes time to build, and only generates cash flows once fully completed. Firms benefit from completing projects faster because they discount future cash flows. They can speed up project completion, but incur ever increasing acceleration costs to do so. At each point in time, firms optimally choose how much to invest on ongoing projects and whether to start new projects. Optimal investment in ongoing projects equates the marginal returns from earlier completion to the marginal costs of acceleration. This intensive margin tradeoff pins down a project's remaining time to build. On the exten-

[1]This interpretation is consistent with a voluminous literature showing that less generous unemployment benefits accelerates re-employment through higher hazards , presumably due to higher search effort (Chetty, 2008; Rothstein, 2011).

sive margin, firms start new projects with positive net present values, internalizing optimal gestation lags. Our framework nests exogenous time to build as a limiting case.

We first explain why our empirical results follow from endogenous time to build. To do so, we take an analytical approach. We map the banking shock (data) to an increase in firm discount rates (model). The mapping is consistent with extensive evidence that the cost of credit rises in episodes of credit supply disruptions; and parsimoniously captures that firms value cash more today relative to tomorrow when credit dries up. Given this mapping, we show that projects close to completion are unambiguously sped up, whereas just started projects tend to be slowed down relative to steady state.

The argument proceeds in two broad steps. We first show that changes in project values following the discount rate shock are given by a duration formula, a familiar fixed-income concept that captures how long it will take to reap back the cash flows of the project. We then show that the investment response balances two opposing effects. First, there is a familiar duration effect: as discount rates rise, project values fall, the more so for projects far away from completion (i.e., large "residual maturity"). Second, there is a novel "acceleration" effect. Investors understand that they can shift project cash flows over time by deciding how fast to build it. This option is more valuable when projects are closer to completion: at a cost, they can be accelerated to start delivering cash flows. Indeed, we prove that the duration effect vanishes as the project ("bond") approaches completion ("maturity"). Hence, for mature projects, acceleration dominates and projects are sped up. For early-stage projects, duration dominates, so it is optimal to slow down the project.

Our empirical and theoretical results qualify the standard intuition that capital expenditures necessarily decrease following adverse shocks to firm financial health. To our knowledge, this upends the conventional wisdom in capital budgeting that an increase in discount rates must be met with lower investment. Capital formation may very well *rise*, as the optimal response to higher interest rates for sufficiently mature projects is to invest more, rather than less. Further, this has implications for interpreting extant evidence on the effect of shocks on capex: aggregation across projects averages positive effects on near-completed projects and the negative effects on nascent or unbegun projects, so the distribution of projects over their implementation stages matters for firm- or aggregate-level investment. Consistent with this channel, Selgrad and Siani (2025) find that contractionary monetary policy shocks lead firms to revise upwards their investment plans in already ongoing projects, but to sharply revise downward plans in their unbegun projects.

To quantify the implications of endogenous time to build for investment dynamics and policy, we enrich the model and take it to the micro-data. We introduce heterogeneity in project returns, sizes, and construction technologies; and estimate structural parameters to match our causal estimates by computing model counterparts to our intensive and extensive margin regression coefficients. We feed discount rate shocks into our quantitative model and

compare investment fluctuations under endogenous versus exogenous time to build, both in partial and general equilibrium.

First, endogenous time to build makes investment dynamics more responsive to shocks, increasing investment volatility by 30% relative to the exogenous benchmark. The total effect hides sizable compositional effects. When time to build is exogenous, investment volatility results exclusively from variation in project starts. When time to build is endogenous, dynamics are instead driven primarily by adjustments in time to build. Hence, endogenous time to build generates endogenous amplification, thereby requiring smaller primitive shocks to generate sizable investment fluctuations.

Second, endogenous time to build generates *state-dependence*: mature and young projects differ in their response to discount rate shocks, so the initial distribution matters.[2] We thus propose a novel source of state-dependence in the effects of monetary policy: interest rate hikes (cuts) will be less contractionary (expansionary) on impact when the distribution is skewed towards more mature projects. This state-dependence is strong , possibly flipping the impact effects of changes in interest rates on aggregate investment.

Third, endogenous TTB provides lessons for investment stimulus policy. With exogenous TTB, temporary tax credits increase investment only through entry. Endogenous TTB introduces an intensive margin channel: investment in existing projects spikes, as firms rush to complete projects before subsidies expire. From a stabilization perspective, tax credits reallocate investment demand intertemporally, thereby providing flexibility to discretionary fiscal policy. Beyond stabilization, investment subsidies have been increasingly deployed to accelerate structural changes (e.g. the renewable tax credits from the Inflation Reduction Act). Our model clarifies how these policies trade-off speed gains with acceleration costs.

Relation to Literature. We follow a tradition in macroeconomics and finance of providing micro facts, elasticities, and structural parameters to discipline industry- or macro-models. Examples in the investment literature include Cooper and Haltiwanger (2006) on adjustment costs; Ramey and Shapiro (2001) and Lanteri (2018) on secondary capital markets; and House and Shapiro (2008) and Zwick and Mahon (2017) on accelerated depreciations bonuses. We supply the same kind of portable objects with our three main contributions: (i) new measurement and causal evidence on how firms adjust capex timelines with wide cross-sectional coverage; (ii) a theoretical framework with sharp comparative statics that overturn conventional capital-budgeting rules; and (iii) a structural model with implications for policy evaluation.

Our paper further to a literature that treats TTB as a driver of real dynamics, dating

[2] As the distribution of projects depends – even in steady state – on policy stances (e.g. the interest rate set by the monetary authority), adjustment costs ubiquitously used in investment models thus become *state-dependent*. Endogenous time to build provides an empirically plausible microfoundation for such costs, and can be readily embedded in models of firm, industry, or aggregate dynamics.

back to Pigou (1920), Aftalion (1927), and Kalecki (1935).[3] Kalouptsidi (2014), Greenwood and Hanson (2014), Oh and Yoon (2020), Gomtsyan (2024) and Oh et al. (2024) study how exogenous TTB drives supply elasticties, return predictability, and boom-bust dynamics in shipping or housing. Lewis and Bajari (2011, 2014), show that contractors accelerate road construction to avoid procurement penalties. Relative to such work, we (i) document quasi-experimental evidence of endogenous TTB in a wide cross-section of industries;[4] and (ii) provide a portable, microfounded model of optimal TTB that extends the neoclassical theory of investment (Hall and Jorgenson, 1967; Abel and Eberly, 1994).[5]

Last, we converse with time-to-build theories of production. Time as a factor of production dates back to Böhm-Bawerk (1889), and has been revisited by Antras (2023). Kydland and Prescott (1982) seminally introduced exogenous TTB to real business cycles.[6] Recent work in macroeconomics has re-emphasized its role: Meier (2020) argues that time-series variation in TTB due to supply chain disruptions yields GDP and TFP losses; Bloesch and Weber (2023) show time to onboard knowledge workers can explain the response of R&D to monetary policy; Liu and Tsyvinski (2023) and Schaal and Taschereau-Dumouchel (2025) study shock propagation in dynamic input-output models. We push a new direction: we study endogenous time to build, providing lessons for both fiscal and monetary policy.

The rest of the paper is as follows. Section 2 describes the data and summarizes our measurement exercises. Section 3 presents the econometric evidence. Section 4 introduces our model and analytical results. Section 5 explains our calibration. Section 6 studies investment dynamics and policy implications. Section 7 concludes. The Online Appendix elaborates on data construction and provides further empirical and theoretical results.

[3] Tangentially, we measure time to build. Early literature relied on small samples or aggregated data from the US (Mayer, 1960; Montgomery, 1995; Brooks, 2000). Millar et al. (2016) measure time-to-plan for retail stores, offices, hotels and warehouses in the US. Glancy et al. (2025) uses the same data source to measure time-to-build and study the role of abandonment options for commercial real estate supply elasticities. We contribute by relying on microdata from multiple industries, sponsors, and project sizes in India, the world's third largest construction market, with $1.7 trillion USD in anticipated investment outlays by 2030 (Invest India). Comprehensive project-level measurement like ours is non-existent for developing economies, to the best of our knowledge.

[4] As a by-product, we add to the literature on real effects of credit supply disruptions by documenting the role of a novel driver of investment responses, namely project maturities. Our empirical strategy also connects with a vast literature that has used quasi-experimental variation to estimate the effects of unemployment insurance generosity on re-employment hazards (Schmieder and von Wachter, 2016).

[5] We incorporate irreversibilities, but abstract from fixed costs. Majd and Pindyck (1987) introduce exogenous time to build in real options (McDonald and Siegel, 1986), showing it can strengthen "wait-and-see" effects (see also Aïd et al. (2015)). We innovate by (i) analytically proving how changes in discount rates and in future cash flows shape optimal project value and investment; and (ii) working with heterogeneous projects, thus studying aggregation and distributional state-dependence.

[6] Earlier, Hall (1977) and Taylor et al. (1982) suggested TTB as microfoundation for adjustment costs and the Samuelson (1939) investment accelerator. Lucca (2007) related exogenous TTB to investment adjustment costs, which help match empirical investment responses (Christiano et al., 2005; Eberly et al., 2012). Casares (2006) and Edge (2007) show TTB has quantitative implications for monetary transmission, while Leeper et al. (2010) and Ramey (2020) show that the potency of fiscal multipliers varies with gestation lags of public investment. None of these papers explore endogenous time-to-build.

2 Data and Measurement

We obtain data on large capital expenditure projects from CapexDx (CMIE, 2023). The data provider defines a project as a construction enterprise where "there is reasonable clarity on the capacity being created". The data includes project name, sponsor, cost, geographical location, and end-user industry from mid-1990s onwards. Examples of projects include steel plants, irrigation canals, airport terminals, office and residential buildings, etc.[7] Crucially, CapexDx "is a monitoring machinery that records the various events that a project goes through in its life-cycle." This event history allows us to observe when projects were announced, implemented, finished (e.g., completed or abandoned), or lost-to-follow-up. We elaborate on project definition rules and data collection in appendix A.1.

Table 1 describes our micro-data on project lifecycles. First, this fills a long-standing measurement gap. Second, it provides context to our quasi-experimental estimates. Panel A presents summary statistics on the cross-section of projects. We observe over 100,000 projects sponsored by over 30,000 entities across a broad range of end-user industries and geographies.[8] The median (average) project is sponsored by a firm with 11 (113) projects. Projects in our data are sizable enterprises: the median project costs 503 million rupees, while projects above the 90th percentile cost over 10 billion rupees.[9] Importantly, projects in our sample are either new units (81%), large expansions (15%) or modernizations (4%) of existing units. They are *not* acquisitions or other forms of secondary market transactions.

Panel B provides an overview of projects' lifecycles. To do so, we construct project histories from event-level data. Multiple difficulties arise in reconstructing a project lifecycle from event-level data, but we ensure that our project histories are sensible, and hence that our results are not driven by measurement error. We elaborate on our extensive data cleaning, including multiple examples, in Appendix A.2.

All projects start when they are announced. The median project spends 3 quarters in this phase. Most projects (70%) move to implementation. The median project spends 4.5 quarters under implementation. At any point during construction, a project may be stalled, abandoned, or completed. The latter account for 40% of all projects in our data (and roughly

[7] Systems of National Accounts usually divide "fixed assets" (the K of macroeconomic models) into structures, equipment, and, more recently, intellectual property. Our data covers structures only. We do not observe replacements or maintenance of existing equipments; nor do we observe capacity or capacity utilization.

[8] To visualize this coverage, the online appendix plots the cross-sectional distribution of projects across sectors and geographies across all years in the data, shows how the sectoral and ownership composition of sample projects evolves over time, and reports the distribution of shares and the HHI across sector, industry, states, and sponsors. The state (industry) HHI is 6% (4%). Sponsors include mostly Indian private firms and state-owned enterprises. Therefore, not all projects in our data are sponsored by firms, but we will use the terms sponsor and firm interchangeably. Note also that though public sponsors account for almost 40% of the projects, most such sponsors are (partially or fully) state-owned enterprises, not government agencies.

[9] The median (average) project costs 7 million (86 million) USD, and the right tail features projects over 140 million USD. Given the large nominal devaluation of the rupee since the GFC, these numbers likely provide a conservative estimate of project costs in USD.

Table 1: Summary Statistics: All Projects

	Mean	SD	10th	25th	50th	75th	90th
Panel A: Cross-Sectional Characteristics							
Projects per Sponsor	113.05	257.90	1.00	2.00	11.00	77.00	366.00
Year Started	2010	8	1997	2005	2011	2017	2020
Last Observed	2014	8	2001	2009	2016	2021	2022
Cost (Rs. Million)	6428.76	40583.47	46.00	125.70	503.30	2500.00	10000.00
Missing Cost	0.29	0.45					
Share: Section	0.19	0.11	0.02	0.07	0.23	0.31	0.31
Share: Industry	0.04	0.04	0.00	0.01	0.02	0.04	0.12
Share: State	0.06	0.04	0.02	0.03	0.05	0.09	0.14
New Unit	0.81	0.39					
Large Expansion	0.15	0.35					
Private	0.57	0.50					
Public	0.38	0.49					
Panel B: Lifecycle Dynamics							
Ever in Status							
Under Imp	0.71	0.46					
Stalled	0.06	0.23					
Completed	0.40	0.49					
Shelved or Abandoned	0.05	0.21					
No Information	0.31	0.46					
Time in Status (Qtrs)							
Announced	6.35	9.41	0.04	0.92	3.32	8.10	15.78
Under Imp	8.74	13.13	0.00	0.00	4.51	12.12	23.62
Stalled	0.69	4.34	0.00	0.00	0.00	0.00	0.00
Number of projects	106626						
Number of firms	32456						

Notes: This table reports summary statistics on all projects available in the March 2022 vintage of CapexDx. Panel A reports cross-sectional characteristics. Shares are computed within a particular sector, industry, or state, and then assigned to projects. Panel B reports lifecycle characteristics. To do so, we leverage our panel dataset tracking project histories. "Ever in Status" variables are dummies that take value 1 if the project was ever in that stage. They need not sum to one, as a project may transit through multiple stages over its lifecycle. "Time in Status" variables measure the total amount of time spent in a particular stage over the project's entire observable history. We only include non-terminal stages, i.e. we exclude completion, abandonment, and loss to follow-up.

60% of projects that move into implementation). Abandoned or stalled projects are rare in our data. As our data ends in March 2022, any projects announced or under implementation at that point are treated as right-censored observations.[10]

Thirty percent of projects are "lost to follow-up". In other words, we do not know what has become of them. CapexDx stops tracking projects "if they are stalled or shelved or abandoned or information regarding them is not available for over 30 months in the case of manufacturing projects and for over 36 months in the case of infrastructure projects." Reassuringly, this right-censoring is not a one-way street: CMIE resumes tracking previously censored projects if it manages to obtain reliable information on project status from the public domain or the project sponsor. The combination of intense monitoring and transparent censoring rules bolsters data reliability. Our econometric strategy will ensure our results are not driven by censoring in the data.

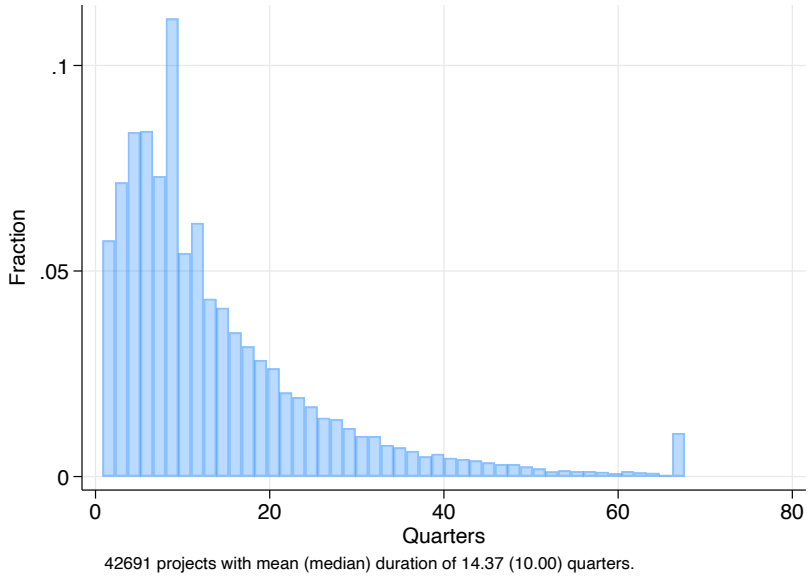
Novel Facts on Time to Build We measure a project's time to build from announcement to completion. For such, we restrict the analysis to projects that are eventually completed. Our results should thus be interpreted under the possibility that completed projects systematically differ from abandoned or censored projects along predictable dimensions. Figure 1 plots the distribution of time to build. The median project takes 2.5 years to be completed. The distribution is right-skewed, with a sizable share of projects taking over 15 years.

The aggregate distribution hides considerable cross-sectional heterogeneity. Figure A3 breaks down the distribution at the sector-level. Transportation and construction feature the longest time to build, whereas retail and information technology feature the shortest. The figure also splits the distribution based on public or private ownership. Public sponsors build projects with longer time to build. This is partly driven by industrial composition: the public sector frequently sponsors heavy infrastructure projects. For example, Indian Railways is the largest public enterprise in India, and railways have notoriously long time to build. Last, Appendix Figure A4 plots the relationship between time to build and project size, as proxied by cost.[11] The elasticity between size and gestation lags appears robustly constant: a 1% increase in costs is associated with a 0.15-0.18% increase in completion times. Appendix Table A4 collects estimates from the regression specifications. Table A5 decomposes the cross-sectional variation with fixed effects. Industry dummies capture about 30% of the variation. Geography and ownership add little additional explanatory power, consistent with a strong

[10] Appendix Table A2 tabulates the frequency of transitions across different stages, excluding no transition events. Most announced projects move into implementation, and most projects under implementation are eventually completed. About 20% of announced projects, 6% of stalled projects, and 27% of projects under implementation are lost to follow-up. Appendix Table A3 instead estimates quarterly transition probabilities between stages including transitions to itself, and shows that intermediate stages are persistent.

[11] Monetary cost provides a common metric to compare projects across different "size" definitions. That is, while it's feasible to compare two residential buildings based on how many floors are being built, it's not as straightforward to compare railways to irrigation canals.

Figure 1: Distribution of Time to Build Across Completed Projects



Notes: the figure plots the histogram of time to build for all completed projects in the Mar 2022 CapexDx vintage. We measure a gestation lag from the first date that a project appears in the data (their announcement date) to its eventual completion. We winsorize the distribution at the 1st and 99th percentile for visualization (but report the mean and median of the raw distribution).

role for technological primitives captured by the project's end-user industry.[12]

With a better understanding of projects' characteristics and lifecycles, we turn to the main empirical question: do firms have some control over how fast they build projects?

3 Testing for Endogenous Time to Build

Testing whether firms can change how fast they complete projects requires us to devise an experiment where we do not alter the natural progression of project completion, but shock the conditions faced by the project sponsor. Consider a scenario where time to build was purely exogenous. At project onset, firms chose an idealized builder, made payments up-front, and once the contract was signed, could not make changes to the construction process. In turn, the builder consistently worked in the project. In the absence of any unforeseen disturbances, time to build would be perfectly known. This thought experiment captures the near-universe of investment models. Whether the firm experienced distress — weak sales,

[12]Industry may fail to proxy exclusively for technological factors. When we include sponsor and year started fixed effects, we account for 58% of the variation in time to build. The sizable within-firm variation may reflect the unpredictability of construction projects(Bajari and Tadelis, 2001) or active management by sponsors of project timelines. A stricter approach would obtain characteristics from engineering blueprints or construction records, which we do not observe. Further, increasing the dimensionality of our predictor set improves explanatory power, but at the cost of less interpretability.

extraordinary expenses, cash shortages, or cuts in credit lines – would have no bearing on project completion. Ex post shocks could cause early or late deliveries by the idealized contractor, but those would be unrelated to any decisions taken by the firm. This is what we mean by "natural progression" of a project. We would *not* be able to reliably detect any relationships between shocks to firms and project completion times in the data, as only unobserved, project-level disruptions would generate variation in completion hazards.

We contrast this null hypothesis against an alternative scenario where firms do have some control over how quickly to finish projects. If times were exceptionally good (bad), firms could speed up (slow down) completion of an ongoing manufacturing plant. In the absence of project-specific disturbances that are correlated with the firm-level disturbance, such episodes would offer encouraging evidence. Firms reacted to the shock by actively managing the portfolio of capital expenditure projects, changing how quickly they completed ongoing projects, a feature we name "endogenous time to build".

Our empirical strategy systematizes the thought experiments above. The key difficulty is to find a shock that affects the firm, but is plausibly unrelated to the daily affairs of project construction. If projects derail because their sponsors are bad firms, it is hard to argue that firms explicitly had some control over the derailment. It could be that bad firms consistently choose projects with worse technological factors, and bad outcomes are likelier to happen to bad firms. That an adverse shock hit the firm at the same time that its project derailed would thus be uninformative about whether the firm could alter time to build.

We circumvent this identification challenge by considering a setting where firms face a contraction in credit supply originated in the banking sector. We trace the shock from banks to firms and examine what happens to firm projects. We leverage variation from firms being differentially exposed to troubled banks; and we will provide evidence that more and less exposed firms were observationally similar before banks got in trouble. If remaining reasons for potential project disruptions are just noise, comparing what happens to projects of more versus less exposed firms tests whether a firm-level shock unrelated to the natural progression of a project led to changes in time to build.

To implement our empirical strategy, we link projects in CapexDx to their sponsoring firms on ProwessDx. The latter data is sourced from regulatory filings and is *not* restricted to private, publicly-traded companies (Alfaro and Chari, 2014). We collect firm- and bank- level financial statements from ProwessDx. We then hand-collect loan-level data from the Indian Ministry of Corporate Affairs (MCA) website. The data approximates a credit registry for secured loans[13], and allows us to link the financial health of firms' banks to the performance of

[13]Most bank lending in India is securitized. Failing to register a secured loan effectively nullifies the benefits of secured lending, thereby incentivizing creditors to register their charges. In cases of borrower restructuring, a secured lender with a registered charge gets priority over a secured lender who failed to register a charge. In cases of borrower liquidation, unregistered secured lenders are treated as unsecured lenders.

firms' projects. For each loan, we observe the amount borrowed, the date of the transaction, as well as borrower and lender name. We do not observe interest rates, contractual maturity, covenants, or any other contractual details on the loan.

Last, we link borrowers in the loan-level data to CMIE datasets by using the unique Company Identification Number of a firm. These identifiers are assigned by the Indian government and present in both datasets, facilitating the matching process. Linking lenders to the CMIE data is more challenging. We can only rely on lender names, which are often misspelled. Using a combination of fuzzy matching algorithms and extensive manual checks, we create a crosswalk between lender names in the MCA data and company names and identifiers in the CMIE data. We are able to match over 90% of our loans (both in terms of loan volume and number of charges) to a Prowess company, thereby identifying the majority of entities lending to project sponsors.

3.1 A Credit Supply Shock: the Indian Asset Quality Review

Our quasi-experimental setting is the Indian Asset Quality Review, a widespread audit of Indian banks. We summarize its main features, closely following Chopra et al. (2020).

Before the Global Financial Crisis, Indian banks had to automatically reclassify restructured loans into non-performing assets and set aside corresponding provisions. On August 27, 2008, the RBI suspended automatic reclassification given global turmoil in financial markets. No additional provisions had to be set for restructured loans, so long as borrowers met restructuring terms. This regime lasted until April 1 2015, despite concerns of evergreening in the banking sector.[14] The Asset Quality Review was the RBI response to these concerns. It was at first a special audit of scheduled commercial banks conducted between August and December of 2015. Following this first inspection, the RBI conducted annual audits under the same guidelines. RBI auditors estimated the amount of non-performing assets in each bank's portfolio, required provisions to be set aside, and mandated that banks disclose audit results in their financial statements.[15] The audits uncovered sizable under-provisioning across systemic banks and thus had the potential to reduce bank lending. Importantly, the RBI did not structure capital infusions or backstops.

[14]Loan loss provisions reduce bank net income, thereby generating incentives to under-report. Banking regulation imposes such policies to align privately optimal bank risk-taking with the ensuing externalities, i.e. increases in systemic risk (Freixas et al., 2015). Consistent with RBI concerns and with the cited theories, Chopra et al. (2020) documented sizable increases in restructurings, but no increases in non-performing assets during the forbearance period.

[15]The reporting requirement was binding either if the additions to provisions exceeded 15% of bank's net profits; or if additions to gross non-performing assets flagged by auditors exceeded 15% of yearly additions to gross non-performing assets flagged by the bank. Chopra et al. (2020) documents that these requirements were mostly binding; that additional provisions and gross non-performing assets were sizable relative to previous net profits and incremental gross NPAs; and that reporting (and thereby troubled) banks accounted for a large share of the overall secured loan volume in the MCA charge registry.

We first confirm that the audits led to a supply-led reduction in credit with borrower (Khwaja and Mian, 2008) or borrower-by-time fixed effects. The fixed effects estimator identifies the effect of the shock on equilibrium loan amounts by comparing more and less exposed banks, holding credit demand fixed. We include lender fixed effects to ensure our estimator is not capturing time-invariant heterogeneity across banks. Rather, the estimator asks whether banks more exposed to the shock differentially cut loans to a particular borrower in a given year, relative to their usual proclivity to extend loans.

We construct a lender-borrower-year panel from the MCA data. First, we isolate all outstanding loans between 2013 and 2015 (pre-audit period) and collect all borrower-lender pairs by summing over different charges. For each pair, we create observations for years 2013-2019. If a pair had an outstanding loan in a given year, we assign it the total amount. If the pair had no outstanding loans in a given year, we assign it zero. The procedure gives us a balanced panel of firm-bank relationships over the sample period, fixing the composition of relationships prior to the audits.

We measure how exposed a bank b is to the audit shock at time t as the difference in provisions resulting from the audit, scaled by total bank assets (Chopra et al., 2020)

$$\text{Bank Shock}_{bt} = \left(\frac{\text{Provisions Required by the RBI Post-Audit} - \text{Provisions Pre-Audit}}{\text{Total Assets}} \right)_{bt}$$

The measure captures that banks who must post more provisions experience larger reductions in lending capital, which should translate into fewer loans. We normalize by bank assets to avoid spuriously comparing large and small banks. We then regress total loans outstanding between lender b and borrower f in year t using a Poisson pseudo-maximum likelihood (PPML) estimator

$$\text{Loans}_{bft} = \exp\left(\gamma \times \text{Bank Shock}_{bt} + \lambda_{ft} + \omega_b + X_{bft}\Gamma\right) \epsilon_{bft}$$

where λ_{ft} are firm-by-year fixed effects that absorb unobservable credit demand shocks, ω_b are bank fixed effects that absorb permanent heterogeneity across banks, and X_{bft} collect other controls. We are interested in γ, the semi-elasticity of equilibrium loan amounts to the bank shock. We cluster standard errors at the lender level.[16]

Appendix Table A6 presents the results. In our preferred specification with lender and

[16]The shock is set to zero if the lender is not a scheduled commercial bank. We include non-SCBs in the sample as borrowers may substitute towards them following the information shock hitting SCBs. The shock also takes value zero for years prior to the start of the special audits. These years provide information on lending dynamics for the affected institutions before the information shock. As for the choice of estimator, a growing literature advocates for PPML in settings where the dependent variable is non-negative and has a large mass of zeros (Silva and Tenreyro, 2006; Cohn et al., 2022). Chen and Roth (2022) proved that one can recover arbitrarily-sized treatment effects by appropriately rescaling the outcome Y in $\log(1+Y)$ specifications estimated by OLS. They explicitly recommend the use of Poisson methods instead.

borrower-by-year fixed effects, we find that a one-standard deviation increase in bank exposure reduces outstanding credit in the average pair by 5.1%. The firm-year fixed effects control for time-varying demand confounders, so the coefficient represents a relative reduction in credit supply among more versus less affected banks. We obtain the same results when we restrict the sample to borrowers for whom we observe projects in the Capex dataset, and whose projects are included in our project-level regressions.[17]

3.2 From Banks to Projects: Estimation and Identification

Having established that the audit shock has bite, we map the banking shock to firms and their projects. If a firm borrows more from troubled banks, it potentially faces starker credit disruptions. We thus model exposure for firm f by aggregating bank-level exposures to the audits, weighting each bank b by its lagged share of total borrowing

$$\text{Firm Exposure}_{ft} = \sum_{b \in B_{f,t-1}} \left(\frac{\text{Loans}_{b,f,t-1}}{\sum_{b \in B_{f,t-1}} \text{Loans}_{b,f,t-1}} \right) \text{Bank Shock}_{bt}$$

To quantify the effect of shock exposure on project completion hazards, we estimate a discrete-time duration model (Van Den Berg, 2001)

$$Completed_{pft} = \exp\left(\beta \times \text{Firm Exposure}_{ft} + X_{pft}\Gamma \right) v_{pft} \tag{1}$$

where p refers to a project, f refers to the project's sponsor (or, firm), t refers to calendar time. Intuitively, conditional on surviving up to period t, completion arrives at a Poisson rate that depends on shock exposure, controls X_{pft} and unobservables v_{pft}.[18] We cluster standard errors at the firm level (Abadie et al., 2022).

Proper identification of β requires that bank shocks are (conditionally) uncorrelated with

[17] Appendix Table A7 reports results from a linear model in first-differences. The semi-elasticities obtained by dividing the coefficients by the mean of the outcome are similar in magnitude to those estimated in Table A6. This specification suggests a greater role for firm-time effects, but the control set included in the regressions with only borrower and year effects approximate well the estimates from the more saturated specifications.

[18] We organize the data into a quarterly panel of projects. The outcome $Completed_{pft}$ is zero in all periods before project completion, and one in the completion period. If a project is right-censored, either because CapexDx loses track of or because the project is ongoing, $Completed_{pft}$ takes value zero. OLS is misspecified due to right-censoring. Restricting our attention to projects for which we observe full histories runs into selection issues: completed projects may systematically differ from censored projects. Duration models explicitly account for right-censoring and therefore do not suffer from such selection issues. The log link implies a semi-parametric, piece-wise exponential model for hazards, which is reasonable given our outcome is the arrival of a rare event (the unconditional completion probability is 4%). Moreover, the non-linear specification ensures that hazards can quickly rise as projects approach completion. Alternatively, one interpret our model as a reduced-form log-linear equation with multiplicative error structure, a now popular estimation strategy in the gravity literature (Silva and Tenreyro, 2006). So long as the conditional expectation function is correctly specified (Gourieroux et al., 1984), the model can be estimated by PPML. Including high-dimensional fixed effects in PPML models with large datasets is feasible due to novel estimation routines (Correia et al., 2020, 2021).

(loan-weighted) project-level unobservables (Chodorow-Reich, 2013). Identification leverages exogenous variation in the shocks. Correlation of the shares $w_{b,f,t-1}$ with unobservables or the outcome does not invalidate the design (Borusyak et al., 2021). Instead, we worry if (1) there are other factors that influence project completion and are correlated with the credit supply shock; and (2) we fail to control for such confounders. Previous research has accumulated convincing evidence on the exogeneity of the credit shock (Chopra et al., 2020, and references therein). We safeguard our analyses by intuiting potential confounders and including them as controls whenever possible.

First, some firms may systematically perform poorly, build projects slowly and build relationships with unhealthy banks who are more likely to underreport non-performing assets. Firm fixed effects address this time-invariant sorting concern. Second, projects in our sample are immobile, which makes them susceptible to regional shocks (e.g., political instability, changes in construction regulations, variation in economic slack or construction labor supply, etc). These factors threaten our design if banks cut credit by internalizing them. We include state-by-year fixed effects to absorb these regional confounders. Third, aggregate or industry-level shocks (e.g. recessions, supply chain disruptions) may delay project completion regardless of firm actions; and may lead bank loans to perform poorly and induce banks to hide losses. We include sector-by-year fixed effects to mitigate these concerns. Fourth, we include a cubic spline on project age, which removes baseline hazards and allow us to (semi-parametrically) compare projects of similar ages. In our most conservative specifications, we further include controls related to recent firm performance in product markets (e.g. sales growth) and firm financial solvency (e.g. leverage), which attempt to span the space of time-varying firm-level factors that could influence both project completion likelihood and bank's propensity to hide losses.[19]

Table 2 presents estimates of model (1). Column (1) starts by estimating a specification only controlling for baseline hazards. Taken at face value, a one-standard deviation increase in project-level exposure to the audit shock increases hazards contemporaneously by 11%. Column (2) tightens identification by including firm fixed effects and project state-by-year fixed effects. A one-standard deviation in project-level exposure now raises hazards by 6.6%, a statistically significant effect. Column (3) shows the results are unaffected by the inclusion of firm-year controls. Column (4) adds NIC sector-by-year fixed effects. The effect size drops to 6%, but remains significant. Column (5) is our preferred specification. The additional

[19]For firms with multiple projects, we rely on within-firm rather than within-project variation. This allows us to strike a compromise between identification and sample size for estimation. Including project-level effects would drop too many observations due to separation concerns arising from the high-dimensional fixed effects. Firm-level fixed effects allow us to absorb substantial confounding variation, while simultaneously allowing to include other fixed effects that control for project-level confounders. Throughout, we use "financial year" fixed effects. The financial year in India runs from April 1st to March 31st of the subsequent year. All financial data is measured at this frequency. Even many official macroeconomic series are released based on financial year.

Table 2: Effects of Firm-Level Credit Supply Shocks on Project Completion Hazards

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure	0.1094***	0.0667**	0.0636**	0.0605**	0.0573**	0.0734***	0.0716***
	(0.0270)	(0.0272)	(0.0273)	(0.0264)	(0.0266)	(0.0264)	(0.0266)
DepVar Mean	0.0397	0.0397	0.0397	0.0397	0.0397	0.0397	0.0397
Observation	122123	122123	122123	122123	122123	122100	122100
Age Splines	✓	✓	✓	✓	✓	✓	✓
Firm FE		✓	✓	✓	✓	✓	✓
State x Year FE		✓	✓	✓	✓	✓	✓
Sector x Year FE				✓	✓		
Industry x Year FE						✓	✓
Firm Controls			✓		✓		✓

Notes: the table reports PPML estimates of the semi-elasticity of project-level hazards to firm exposure to the Asset Quality Review (see model (1)). The sample consists of projects observed quarterly between 2013-2019. Firm exposure is defined as the weighted-average of lender exposure, where weights correspond to outstanding loans in the previous year. Coefficient estimates are interpreted as the percent effect on the outcome for a one standard-deviation increase in firm exposure. For example, column (1) reports that moving from a firm with average exposure to a firm with one-standard deviation higher exposure increases the hazard by 10.94%. Age splines refer to cubic splines on a project's age (measured in quarters). Firm controls include sales, sales growth, profitability, debt over equity, book leverage, equity issuances, cash over liquid assets, and debt over EBITDA. All firm controls are winsorized at the 1st and 99th percentile, and then standardized. All firm controls are lagged by one-period. The reduction in sample size from columns (5) to columns (6) and (7) results from separation of additional observations by the more granular industry-by-year fixed effects relative to the sector-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

firm-level controls barely moves the point estimate: hazards increase by 5.7%, a significant effect. Last, columns (6) and (7) replace sector-by-year with industry-by-year fixed effects. If anything, the tighter specifications yield larger completion effects.

We interpret our hazard estimates as evidence of project acceleration. This parallels a voluminous literature on unemployment dynamics in labor and public economics. Spikes in re-employment hazards around unemployment insurance benefit expirations have provided an empirical foundation for search-based theories, despite search effort often being unobservable.[20] Our empirical evidence follows the same spirit: though we do not observe firm's investment rates (search effort) throughout the life of the project (unemployment spell), hazard estimates provide an empirical ground for the theory of endogenous time to build (unemployment duration). We later describe robustness tests and narrative checks that corroborate this interpretation.

3.3 Extensive Margin Results

Firms discount future cash flows, so accelerating completion increases the project's net present value. If it was costless to speed up, firms would always do so. By revealed preference, speeding up must be costly. But our results document that firms are engaging in costlier behavior in times of low credit supply. If speeding up ongoing projects is costly, and firms can cut down investment on other margins, we would expect to see a decline in new project starts. We test for this extensive margin channel by collapsing the data to the firm-year level and estimating by PPML

$$\text{New Project Starts}_{ft} = \exp\left(\beta \times \text{Firm Exposure}_{ft} + X_{ft}\Gamma\right)\nu_{ft} \tag{2}$$

where ν_{ft} is a residual and X_{ft} collects firm fixed effects, year fixed effects, and time-varying firm-level controls. We cluster standard errors at the firm level.

Table 3 collects results. In a bivariate specification (column 1), a one-standard deviation increase in firm-level exposure reduces new project starts by 7.7%. Adding firm and year fixed effects (column 2) reduces the point estimates to 7%. Further adding time-varying firm controls barely moves the point estimates. In columns (4) and (5), we replace year fixed effects by NIC sector x year fixed effects to control for sector-specific shocks. In our preferred specification (column 5), a one-standard deviation increase in exposure reduces new project starts by 7.6%. Replacing sector-by-year with division-by-year effects slightly reduces the

[20] Dating back to Moffitt (1985) and Katz and Meyer (1990), exit rates from unemployment have been shown to spike close to benefit expiration. These and many follow-up estimates have been interpreted as evidence of endogenous search effort by job seekers and used to quantify the moral hazard costs of unemployment insurance (Chetty, 2008; Kroft and Notowidigdo, 2016). Our empirical design is closest to Rothstein (2011), who quantified the effects of unexpected UI duration extensions on unemployment exit hazards and explored heterogeneous effects by spell duration.

Table 3: Effects of Firm-Level Credit Supply Shocks on Project Starts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure	-0.0775***	-0.0698**	-0.0670**	-0.0806**	-0.0763**	-0.0584*	-0.0588**
	(0.0286)	(0.0325)	(0.0322)	(0.0316)	(0.0314)	(0.0299)	(0.0296)
DepVar Mean	0.8362	0.8362	0.8362	0.8362	0.8362	0.8326	0.8326
Observations	8994	8994	8994	8994	8994	8869	8869
Firm FE		✓	✓	✓	✓	✓	✓
Year FE		✓	✓				
Section x Year FE				✓	✓		
Division x Year FE						✓	✓
Firm Controls			✓		✓		✓

Notes: the table reports PPML estimates of the semi-elasticity of firm-level project starts to firm exposure to the Asset Quality Review (see model (2)). The sample consists of the Capex-Prowess matched sample of firms observed yearly between 2013-2019. Firm exposure is defined as the weighted-average of lender exposure, where weights correspond to outstanding loans in the previous year. Coefficient estimates are interpreted as the percent effect on the outcome for a one standard-deviation increase in firm exposure. For example, column (1) reports that moving from a firm with average exposure to a firm with one-standard deviation higher exposure reduces project starts by 7.75%. NIC Section and Division classifications are constructed from NIC codes and categorizations. Firm controls include sales, sales growth, profitability, debt over equity, book leverage, equity issuances, cash over liquid assets, and debt over EBITDA. All firm controls are winsorized at the 1st and 99th percentile, and then standardized. All firm controls are lagged by one-period. The reduction in sample size from columns (5) to columns (6) and (7) results from separation of additional observations by the more granular division-by-year fixed effects relative to the section-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

point estimates to 5.8%. All effects are significant at conventional levels. Reassuringly, the magnitudes are stable across specifications.

3.4 Heterogeneous Effects

Our results thus far show that, on average, ongoing projects are sped up but new projects are cut back when credit dries up. But intuitively, ongoing projects that were just started should be similar to unbegun projects that were about to be started. Further, as time passes, these just-started projects would have matured. If the same shock happened again, the intensive margin regressions suggest they would have been accelerated rather than cut back. This suggests that effects should be heterogeneous depending on how far along a given project is in its implementation. With the benefit of foresight, that's precisely the sharp prediction that our model of endogenous time to build will deliver. For now, we take this prediction as given and provide supportive evidence in its favor.

Testing for heterogeneous treatment effects runs into two challenges. First, we do not observe whether a project is, say, 30% versus 70% implemented. Second, we cannot observe counterfactual stages beyond the measured stage at the time of the shock, as the project cannot simultaneously be in two distinct stages. We address the first challenge by constructing a proxy measure of project stage. We define the proxy stage as the project's age when entering

the hazard regression sample[21], relative to an ex ante, predicted measure of its time to build

$$\text{Stage}_p = \frac{\text{Initial Age}_p}{\text{Predicted Time to Build}_p}$$

The intuition is that, fixing a project's expected time to build, older projects are expected to be at a more advanced stage; conversely, fixing a project's age, projects with shorter average time to build are expected to be at a more advanced stage.

Since we do not observe expected time to build, we predict it in a preliminary step. We isolate all completed projects in CapexDx that are not included in the regression sample. For these projects, we regress time to build on exogenous predictors. We estimate different regressions, and compare them by assessing their R^2 in our regression sample. We pick the model with highest out-of-sample R^2, which turns out to be a model including industry dummies. Appendix Table A14 and Appendix Figure A14 expand on the prediction exercise.

Having estimated the proxy stage variable, we standardize it and include it along with its interaction with the firm exposure variable in model (1). Table 4 collects results. Across specifications, the results are supportive of the model's predictions. For the project at the mean proxy stage, a one-standard deviation increase in exposure raises the hazard by roughly 9%. If the project stage had been one standard deviation above (below) the mean, the effect would have been increased (reduced) by roughly 7.5%, so the total effect of the should would have been 15.5% (2.5%). In Appendix Table A15, we find similar results if we don't scale initial age by predicted time to build, suggesting our results are not driven by the prediction step.[22]

3.5 Threats to Identification

Our empirical design is valid if the control set ensures that the identification condition holds. Confounding would result if there existed factors that (i) influence project completion and correlate with the credit supply shock; (ii) *and* that we fail to control for.[23]

[21] We prefer to use age when entering the hazard regression over age at the time of shock. Some projects may enter and leave the sample entirely before or after the start of the asset quality review audits; therefore we cannot define age at time of the shock for these projects, but we can always define the age at the time it enters the sample. Moreover, since we include initial age and year fixed effects in the regressions below, one can always partly "reconstruct" what would have been age at the time of the shock.

[22] The effects are significant at conventional levels regardless of the proxy we use for project stage, but we must be cautious interpreting the inferential step when scaling by predicted time to build given we do not account for sampling uncertainty in the prediction step. The fact that the estimates remain significant in Appendix Table A15 suggests that ignoring the noise introduced by the prediction step is not compromising inference.

[23] We focus on our discussion on threats to identification. We provide a battery of econometric robustness exercises in Appendix C. Tables A8 and A10 show that our choice of weights for aggregating the bank shocks is conservative: using pre-period weights instead strengthens the results. Tables A9 and A11 reassures our results are not driven by the choice of estimator: semi-elasticities obtained by dividing point estimates of linear models by dependent variable means are similar to the PPML estimates. In unreported results, we also find robustness to other combinations of fixed effects and analyses windows; and find that our specification captures well effect dynamics, as effects on hazards are largest on impact and decline over time. The short-lived effect on hazards,

Table 4: Effects of Exposure by Proxied Stage

	(1)	(2)	(3)	(4)
Exposure	0.090***	0.086***	0.094***	0.090***
	(0.025)	(0.025)	(0.025)	(0.025)
Stage x Exposure	0.068***	0.069***	0.078***	0.079***
	(0.021)	(0.021)	(0.023)	(0.023)
Initial Age FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
State x Year FE	✓	✓	✓	✓
Sector x Year FE	✓	✓		
Industry x Year FE			✓	✓
Firm Controls		✓		✓

Notes: the table reports PPML estimates of the semi-elasticity of project-level hazards to firm exposure to the Asset Quality Review. The sample consists of projects observed quarterly between 2013-2019. Firm exposure is defined as the weighted-average of lender exposure, where weights correspond to outstanding loans in the previous year. The proxy for stage is constructed as age of the project when first observed in the sample divided by its predicted time to build. This measure is winsorized at the 1st and 99th percentile, and then standardized before being included in the regression model. See the main text and Appendix Table A14 for details on the prediction step. The coefficient on exposure is interpreted as the percent effect on the outcome for a one standard-deviation increase in firm exposure for the project with mean proxy stage. The coefficient on the interaction is interpreted as the change in the main effect resulting from a one-standard deviation level change in proxy stage. For example, the first row in column (1) reports that moving from a firm with average exposure to a firm with one-standard deviation higher exposure increases the hazard by 9% for the project at the mean proxy stage. The second row in column (1) reports that if the project had been one standard deviation above (below) the mean stage at the time of the shock, the effect would have incresed (declined) by 6.8%, for a total effect of 15.8% (2.2%). In order to avoid strong collinearity concerns between the age spline, initial age, and the time fixed effects, we omit the age spline, control non-parameterically for the initial age, and further include dummies for quartiles of the proxy stage. Firm controls include sales, sales growth, profitability, debt over equity, book leverage, equity issuances, cash over liquid assets, and debt over EBITDA. All firm controls are winsorized at the 1st and 99th percentile, and then standardized. All firm controls are lagged by one-period. The reduction in sample size from columns (1) and (2) to columns (3) and (4) results from separation of additional observations by the more granular industry-by-year fixed effects relative to the sector-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

A first concern is the absence of firm-time effects in model (1). Suppose there were unobservables that (i) banks internalized and conditioned on when reducing credit, and (ii) made firms less willing to start projects, but, somehow, more willing to complete ongoing projects. The question then is how well does our control set span the space of time-varying firm-level confounders. We follow Khwaja and Mian (2008) and Chodorow-Reich (2013) and use the results from our credit regressions as suggestive evidence on the absence of unobservable firm-year confounders. If borrower-year unobservables were the chief sources of confounding, moving from borrower-year to borrower and year fixed effects in Table A6 would change point estimates considerably. Instead, estimates barely move: firm and year effects approximate well the information set spanned by the full suite of firm-year effects. Given we include firm and year fixed effects in our preferred specifications, we do not believe our results are driven by unobservable firm-year confounders. To further alleviate this identification concern, we present balance checks in Appendix Table A13. If our exposure measure predicted pre-audit firm characteristics, we would be concerned that banks were differentially cutting credit on these observables. We regress one-period lagged firm characteristics on a contemporaneous measure of exposure, including firm and year effects since we rely on within-firm time-series variation in our design. We detect predictability for profitability and cash over assets, but fail to detect predictability among other covariates.[24] Regardless, we include all these covariates as controls.

A second concern is concentrated bank lending. If some firms are a large share of a bank's charges, a shock to these firms could induce banks to hide losses, thus challenging quasi-randomness of the bank shock. Appendix Figure A15 shows this is not the case. It plots the distribution of the firm shares in bank charges (i.e., $Loans_{b,f,t}/\sum_{f'} Loans_{b,f',t}$), showing that most firms comprise a small share of the total charges registered by lenders. Further contrary to these concerns, Appendix Figure A15 shows a robustly negative correlation between bank lending concentration and future bank shocks. That is, banks that were most exposed to the audit shock are those that had less concentrated lending portfolios. These correlations hold both for firms in our regression sample, and for the larger universe of charges.

A third, more subtle identification concern, is that the shock could change the ability of the data provider to collect data on projects. This possibility opens up space for a delicate form of selection bias: the sample of projects collected after the shock may differ from the sample of projects before the shock. We would not be able to make causal statements if the treatment induced such differential censoring. In Appendix D, we provide two analyses to

however, translate into longer-lived effects on survival functions that persist one-to-two years out, so that our effects on capital formation are meaningful beyond impact horizons.

[24] We also run cross-sectional balance tests. In column (3) of Table A12, we regress pre-audit firm characteristics on average exposure ex post. We detect cross-sectional predictability in sales and equity issuance, but fail to detect predictability otherwise. Note that this test is more stringent that what's required by our identification assumption, but is overall encouraging.

soothe these concerns. First, we restrict our completion analyses to projects that were in data vintages *prior* to the first audits. Even if the data collection process changed across treated and untreated units following the shocks, projects in vintages prior to the shock would not have been affected by these changes. The sample is thus immune to the selection concern. Second, we test a direct implication of differential censoring due to differential backfilling across treatment groups. If CapexDx had become less able to backfill data on treated relative to untreated projects, we should observe a downward trend in the number of treated projects relative to untreated projects before the shock. We thus test whether exposure predicts differential pre-trends in firm-level project stocks. Across the two tests, we find no evidence that our results are driven by differential censoring.

A final concern is that some projects could have had their scopes reduced after the shock, in which case a positive effect on the completion hazard could reflect a reduction in time to build even if it was purely exogenous. In Appendix E, we alleviate this concern surrounding the interpretation of our estimands. First, we provide qualitative evidence on the construction industry, arguing that commonly used contracts and technical considerations hinder changes in scope of ongoing projects. Such frictions are more pronounced for large capex projects undertaken by sizable sponsors, as in our sample. Second, we repeat our analyses discarding projects who are proxied to be most susceptible to potential reductions in scope. We classify such projects based on how the data provider keeps track of changes in project scopes when collecting the raw data; or based on technological or regulatory aspects of construction that preclude large variations while the project is ongoing. Across these quantitative exercises, our results are similar to our baseline, supporting our preferred interpretation that firms are speeding up project completion.[25]

One concern we cannot speak to is changes to project quality. This is due to data limitations (e.g., we do not observe whether a building's sinks are marble or ceramic.) If sponsors responded by reducing input quality, and if low-quality inputs have lower exogenous lead times, projects could be completed faster. This story could threaten identification if banks differentially cut credit to firms based on their ability to accelerate projects via this quality downgrading channel. We find this unlikely. Further, it could be interpreted as a form of endogenous time to build (substituting inputs to complete faster), though not one that accords with the theoretical model we will use to rationalize the data.

It's worth highlighting that media coverage at the time provides textual corroboration for our econometric findings. The Economic Times, a leading news sources in India, reported in May 2016 how "(...) builders too are feeling the heat with cash flow drying up and banks

[25] An apparent threat to our interpretation is that changes in completion hazards are driven by local input availability. If the credit shock leads some companies to cut back on projects, localized inputs are then freed up presumably at lower cost, which would spur other companies to speed up their ongoing projects. But this is still consistent with endogenous time to build. Further, the presence of state-by-time fixed effects absorb these equilibrium effects from local input markets, and hence our estimates are unlikely to be driven by such forces.

no longer ready to play ball. So, the only option they now have is to complete projects.", with builders "trying to rope in private equity funders (...) ask[ing] for astronomically high returns – in the range of over 25%"; and in May 2015, how "banks were not healthy and their NPAs were rising", with builders "focusing on completing projects which will then unlock cash flows that are locked in." Companies mentioned "high cost funds which we are using to finish projects. These do lower our margins but the focus is on trying to complete projects"; and "not launching projects and phases but rather concentrating on construction and delivery of existing sold projects".[26]

Last, we touch on external validity. We believe the mechanism is operative in other contexts, as anecdotal evidence of endogenous time to build abounds. During World War II, the US accelerated the Pentagon's construction with workers on site around the clock and cost escalations (Goldberg, 1992; Vogel, 2007; Rollo, 2024). In 2016, spurred by demand and tax incentives, Tesla "doubled the number of people constructing the "gigafactory," (...) 1,000 workers build seven days a week on two shifts in an effort to start churning out lithium-ion cells"(Ramsey, 2016). In short, our robustness checks and corroborating narratives reinforce our main findings. We now formalize the economic theory behind our econometric evidence.

4 A Theory of Investment with Endogenous Time to Build

We rationalize our empirical findings by developing a theory of investment with endogenous time to build. By endogenous, we mean that the firm *chooses* time to build, rather than treating it as an exogenous primitive. Our model is minimalist. It allows us to make analytical statements that cleanly spell out the intuition for our results. Yet, it lends itself to quantitative applications with some further enrichments, which we defer to section 5.

Setup Time is continuous and indexed by t. A firm manages a collection of capital investment projects.[27] The firm's discount rate is given by $r > 0$. Each period, a continuum of projects become available. Completing a project requires investing an amount $\bar{x}$. After the project is finished, say at time T, the firm obtains z units of capital, drawn at project inception from a p.d.f. $f(z)$. Capital is valued at a common price p, which firms take as given.

[26]The article names aptly summarize the gist of the narratives: "Low on stock markets: Cash-strapped realty firms run from pillar to post to raise funds" (ET 2015) and "Speeding up delivery only way out for cash-strapped builders" (ET 2016). Though the articles focus on real estate developers, they corroborate our econometric estimates. We also read through selected earnings calls from listed firms that appear on our regression sample. Appendix F presents some quotes. We found examples among firms in manufacturing, energy, etc, some of which mentioned unlocking cash flows faster as a reason for expediting projects. Though systematic narrative evidence is beyond the scope of this paper – our main econometric evidence comes from our quasi-experimental hazard estimates – the quotes exemplify how firms discuss project timelines and expedited completion.

[27]The model's interpretation is the same whether projects are managed by a single firm or by many firms sharing the same structural primitives. Alternatively, one can think of a firm being a project, and use the framework to study industry (Kalouptsidi, 2014) or macroeconomic dynamics.

We relax this assumption and prove that our analytical results hold in appendix H.3. Project returns are pz and only accrue upon project completion. Our setting incorporates project heterogeneity in returns rather than size, an assumption we relax in Section 5. Last, there is no risk. We relax this assumption and prove that our analytical results hold in appendix H.4. We focus first on a partial equilibrium setting.

Let $i(t)$ be how much the firm spends on the project in period t. Normalize the start time of the project at $t = 0$. The project is then completed at the time T that satisfies

$$\int_0^T i(t)dt = \bar{x} \tag{3}$$

Equation (3) states projects are completed when investment flows add up to total size. Suppose p, z and r are constant (ie. as in a steady state). The firm chooses a sequence of investment flows $i(t)$ and a completion time T to maximize the net present value (NPV) of the project subject to (3)

$$\max_{i(t),T} e^{-rT}pz - \int_0^T e^{-rt}\left[i(t) + \kappa(i(t))\right]dt \quad \text{s.t.} \int_0^T i(t)dt = \bar{x} \tag{4}$$

We introduce frictions into the construction process, modeled as additional costs $\kappa(i)$, assumed to be weakly increasing and weakly convex.[28] The frictional costs $\kappa(i)$ do not contribute to installed capacity, i.e. they are deadweight losses. The convex element captures many other complexities of construction. For instance, κ can capture congestion costs: building a factory is faster if more workers are putting up walls and laying down wires, but workers eventually start to bump heads. κ could also stand for moral hazard concerns. Suppose it is costly for contractors to exert effort; and that effort is not contractible (or, if so, not verifiable). In a second-best world, costs unrelated to capacity installation arise, since workers must be incentivized to exert effort. Additional stories for κ are plenty: costs associated with overtime pay, renegotiating contracts, speeding up deliveries, facing a convex labor supply curve for construction workers, etc (Bajari and Tadelis, 2001).

Whenever necessary (i.e. in quantitative exercises), we assume that $\kappa(i)$ has the following functional form (none of our analytical results rely on the functional form):

$$\kappa(i) = \begin{cases} 0 & , i \leq \bar{i} \\ \frac{\kappa}{2}(i - \bar{i})^2 & , i > \bar{i} \end{cases}$$

[28] In the absence of frictions, the solution is trivial: build positive NPV projects instantaneously, and discard negative NPV projects. To see why, note that for any fixed T, the firm minimizes the NPV of construction costs. Since $r > 0$, it is optimal to invest $\bar{x}$ immediately. Discounted profits are then given by $e^{-rT}(pz - \bar{x})$, which are maximized at $T = 0$ so long as $pz > \bar{x}$. If $pz < \bar{x}$, the firm does not build the project. This is counterfactual. Physical capital is not built in a day, as the data shows $T > 0$ for most projects.

The firm can invest without incurring any additional costs up to some upper threshold $\bar{i}$. We interpret $\bar{i}$ as a natural rate of project completion. Beyond this point, accelerating incurs a quadratic cost parametrized by κ. Our model nests one with exogenous time to build as $\kappa \to \infty$, in which case all projects are completed in $T = \bar{x}/\bar{i}$ periods.[29] The exogenous case illustrates how $\kappa(\cdot)$ can stand for a technological constraints on the rate at which the project can be completed.

Optimal Investment Towards a recursive representation, let $x(t)$ denote the state of the project

$$x(t) = \int_0^t i(s)ds \tag{5}$$

Projects are heterogeneous with respect to project stage x and project-specific returns z. We write the firm problem as a Hamilton-Jacobi-Bellman (HJB) equation with state x

$$rv(x,z) = \max_{i \geq 0} -i - \kappa(i) + i\frac{\partial v(x,z)}{\partial x} \tag{6}$$

and terminal condition

$$v(\bar{x},z) = pz \tag{7}$$

The HJB characterizes optimal firm behavior. The flow value of a project to the firm is $rv(x,z)$. When the firm behaves optimally, it trades off the costs and benefits of investment. Costs are born today: placing i units towards the project costs $i + \kappa(i)$. Benefits accrue only when projects are completed. But projects close to completion are more valuable, since the firm is closer to reaping returns. More investment today thus raises the future value of the project. When time intervals are small, the marginal benefit of investing i is given by $\partial v(x,z)/\partial x$, so that the increment to the project's continuation value is $i\partial v(x,z)/\partial x$. The terminal condition restates that a completed project returns pz.

Since $\kappa(i)$ is differentiable, the necessary condition for an optimum is

$$1 + \kappa'(i) = \frac{\partial v(x,z)}{\partial x} \tag{8}$$

so the firm invests up to the point that the marginal cost of investment inclusive of acceleration costs equals the marginal benefit of moving the project forward – a project-level marginal q (Abel, 1981; Hayashi, 1982). With slight abuse of notation, we denote by $i(x,z)$ the resulting policy in the state space. We solve the HJB (6) numerically using finite-difference

[29] The exogenous TTB formulation is inconsistent with our empirical findings under the assumption of optimizing firms. If firms speed up, they increase i following the shock. This would require that they were investing $i < \bar{i}$ at the time of the shock, increasing their investment to $i = \bar{i}$ at the time of the shock. But then, firms would not have been optimizing. This model is consistent with the data only if the credit supply shock increases the technological primitive $\bar{i}$. We find this explanation unlikely.

methods (Achdou et al., 2021).

Optimal Entry Firms optimally start new projects. For any drawn z, the firm can compute the NPV $v(0, z)$. If the NPV is positive, the firm will start the project. This pins down a rule for optimal entry:[30] start all projects with high enough return $z > \bar{z}$, where the break-even point $\bar{z}$ satisfies

$$v(0, \bar{z}) = 0 \tag{9}$$

Distribution of Projects Firms manage multiple projects. As firms invest, project stages change. The distribution of projects over stages thus evolves over time. Let $g(x, z)$ denote the steady state distribution. It satisfies a Kolmogorov Forward Equation (KFE)

$$\forall (x, z),\ \frac{\partial}{\partial x}\left[i(x, z) g(x, z)\right] = 0 \tag{10}$$

The intuition for the KFE is simple. The investment policy $i(x, z)$ is the speed according to which firms move along the x dimension. The flow of firms through a given point x is, therefore, $i(x, z)g(x, z)$: the product of the density of firms at this point and the velocity with which they travel. In steady state, the flow of firms through any given point must be constant, which is equivalent to equation (10).

Now recall that a a constant flow $f(z) \cdot 1\{z \geq \bar{z}\}$ of projects with productivity z enters the economy at each instant.[31] This implies that, in steady state, we must have $g(x, z)i(x, z) = f(z) \cdot 1\{z \geq \bar{z}\}$, which gives us

$$\forall (x, z),\ g(x, z) = \frac{f(z) \cdot 1\{z \geq \bar{z}\}}{i(x, z)} \tag{11}$$

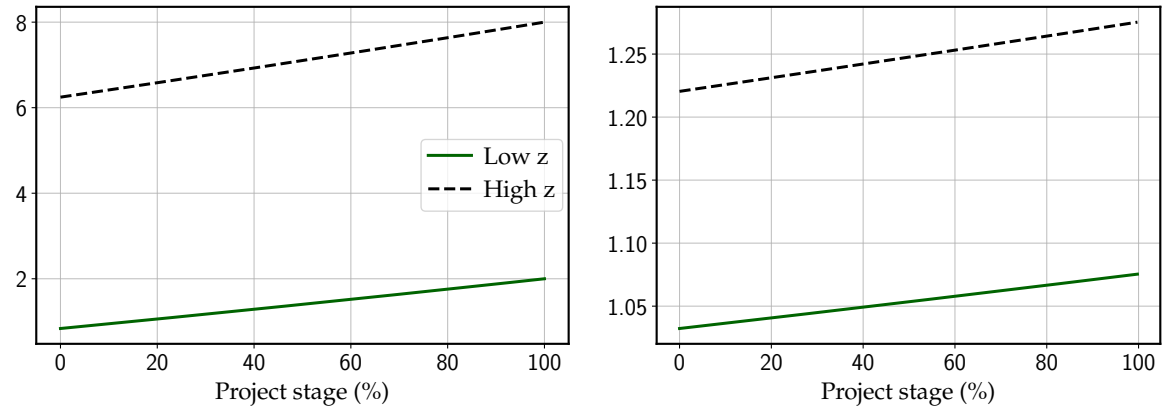
Completion Times Optimal investment $i(x, z)$ tells us how quickly we are installing capacity. We also know how much more capacity we must install to complete the project. Therefore, we can compute how much time remains until project completion, which we denote $T(x, z)$. Solving the steady state Kolmogorov Backward Equation (see Appendix H) with an appropriate terminal condition $T(\bar{x}, z) = 0$ yields

$$T(x, z) = \int_x^{\bar{x}} \frac{1}{i(y, z)} dy \tag{12}$$

[30] Soon, we will linearize the model and study first-order dynamics around a steady state. To do so while preserving an extensive margin, we introduce stochastic fixed costs of entry. The firm pays an entry cost distributed uniformly on $[0, \epsilon]$. The distribution allows us to convexify the problem and proceed with differentiable methods. We set ϵ to be small, so the fixed cost has insignificant effects on the steady state.

[31] Note that the total mass of ongoing projects is not required to be 1 and is later going to vary over time following shocks.

Figure 2: Steady state objects as functions of project stage



(a) Value function $v(x,z)$ (b) Optimal investment $i(x,z)/\bar{\imath}$

Note: the figures plot the steady state solution of the model. Panel (a) plots the value function $v(x,z)$ and panel (b) plots the investment policy $i(x,z)/\bar{\imath}$. The x-axis is the project stage, defined as $100 \times x/\bar{x}$. Solid green lines represent low output projects ($z = 2$); black dashed lines represent high output projects ($z = 8$). Parameters are set at the median values obtained in our calibration in section 5: $r = 0.01$, $p = 1$, $\bar{x} = 1$, $\bar{\imath} = 0.083$, $\kappa = 30.1$.

An analogy to classical mechanics helps here. In a small time interval dt, a firm increases its project state by $dx = i(x,z)dt$. The time necessary to move dx units in the x dimension is, then, $dx/i(x,z)$. The total time until completion adds up these small time intervals until the projects reaches $\bar{x}$. (12) states this formally.

Steady State Solution Figure 2 shows steady state objects as a function of project stage ($100 \times x/\bar{x}$) for $z = 2$ and $z = 8$, and illustrative parameter values. Panel (a) shows the value function. It is monotonically increasing and reaches the terminal value pz at $x = \bar{x}$. Panel (b) shows optimal investment relative to $\bar{\imath}$. We can see that optimal investment is endogenously higher for more productive projects, reflecting the higher payoff at completion. Appendix Figure A22 reports the distribution and time to completion as a function of stage.

4.1 Dynamics

To map our model to the empirical results in sections 3.2 and 3.3, we characterize the response of optimal investment policies to a credit shock. We model the credit shock as an increase in the firm's discount rate r. Appendix H.6 discusses theoretical channels and empirical evidence supportive of this mapping.[32] Intuitively, as credit dries up, debt becomes

[32]There, we also briefly sketch a microfoundation linking provisioning shocks to discount rates. Abstracting from the banking microfoundation in the main model allows us to focus on endogenous time to build for real investment, where our main contribution lies. Further, the change in discount rates may arise through other channels, which may be quantitatively important. Our estimation strategy will allow us to be agnostic over which channels matter most.

costlier (e.g., banks raise rates). Our observed empirical patterns – and therefore the basic theory of endogenous time to build – can arise from a neoclassical framework under a more comprehensive view of discount rates.[33]

Mathematically, we specify a perfect-foresight AR(1) path for discount rates, i.e. $r(t) = r + se^{-\rho t}$. Let $\mathcal{V}(x,z,s,t)$ and $\mathcal{I}(x,z,s,t)$ be the value function and investment policy following the shock, respectively, which depend on the shock size s and calendar time t. We have the following result:

Lemma 1. *The first-order responses of the value function and investment policy to the shock are given by*

$$\mathcal{V}(x,z,s,t) = v(x,z) + se^{-\rho t}\hat{v}(x,z) + o(s)$$

$$\mathcal{I}(x,z,s,t) = i(x,z) + se^{-\rho t}\hat{i}(x,z) + o(s),$$

where

$$\hat{v}(x,z) = \left.\frac{\partial \mathcal{V}}{\partial s}\right|_{t,s=0} \quad \hat{i}(x,z) = \left.\frac{\partial \mathcal{I}}{\partial s}\right|_{t,s=0},$$

and $v(x,z)$ and $i(x,z)$ are the steady state value function and investment policy, respectively.

Proof. See appendix H for all proofs. □

Lemma 1 allows us to characterize value functions and investment policies analytically following the shock up to first-order as deviations from steady state. Analytical tractability stems from separating the time-dependent terms ($e^{-\rho t}$) from terms related to project stage x and productivity z. We start by characterizing the response of the project's value.

Proposition 2. *The first order response of project value is given by*

$$\hat{v}(x,z) = -\left(\frac{1-e^{-\rho T(x)}}{\rho}\right)e^{-rT(x)}pz + \int_0^{T(x)}\left(\frac{1-e^{-\rho\tau}}{\rho}\right)e^{-r\tau}\left[i(y(\tau),z) + \kappa\left(i(y(\tau),z)\right)\right]d\tau, \tag{13}$$

and, as $\rho \to 0$,

$$\lim_{\rho\to 0}\hat{v}(x,z) = -T(x)e^{-rT(x)}pz + \int_0^{T(x)}\tau e^{-r\tau}\left[i(y(\tau),z) + \kappa\left(i(y(\tau),z)\right)\right]d\tau,$$

[33] The neoclassical chassis further clarifies that our empirical and theoretical results are not predicated on the particular form that financing frictions may take (for example, asset- vs earnings-based constraints). In Appendix H.7, we assess whether a model with borrowing constraints can rationalize our empirical findings, and elaborate on why we prefer the discount rate shock formulation. Additionally, and perhaps most pragmatically, this computationally tractable choice allow us to carry out meaningful estimation and counterfactual exercises focusing on the two main novelties of our paper: the theoretical modeling of endogenous time time build, and the rich disaggregated project-level data that can discipline it.

where $y(\tau)$ is the stage of a project that starts in x after τ periods, i.e.

$$\dot{y}(\tau) = i(y(\tau), z), \text{ subject to } y(0) = x.$$

The limiting case of a one-time shock to discount-rates ($\rho \to 0$) is particularly illustrative. Project value changes by its **duration**. To compute the change in project value, we take a weighted sum of time periods over the remaining life of the project. We weigh each time period by the NPV of cash flows accruing in the time period.[34] We use the steady state investment flows and remaining time to build to compute duration.

Intuitively, duration gives us how long it will take to reap back the cash flows of the project. Different from standard fixed income securities, a project requires outlays over its lifetime in order to yield a large terminal payoff. Similar to many fixed-income instruments, the cash flow paid at maturity is large relative to near-term coupons. As interest rates rise, project values fall. But they fall ***more*** for projects whose cash flows will only be received further out in the future. Just like longer duration bonds suffer more from interest rate increases, ***longer time to build projects suffer more from increases in discount rates***. Duration is a crucial input for understanding the response of investment to discount rate shocks:

Proposition 3. *The first order response of the optimal investment policy is given by*

$$\hat{i}(x,z) = \frac{1}{\kappa''(i(x,z))} \cdot \frac{\partial}{\partial x}\hat{v}(x,z), \tag{14}$$

where

$$\frac{\partial}{\partial x}\hat{v}(x,z) = \frac{1}{i(x,z)} \left[\underbrace{v(x,z)}_{\text{Acceleration}} + (r+\rho) \underbrace{\hat{v}(x,z)}_{\text{Duration}} \right] \tag{15}$$

Proposition 3 characterizes how to re-optimize investment plans following a change in discount rates. Equation (14) simply equates the marginal cost to the marginal value of reducing the project's duration, which in turn captures the marginal value of bringing the project closer to completion. How does this change alter the discount rate shock? Equation (15) shows two opposing effects. First, investors become more accelerationent, and therefore value receiving cash flows earlier. This effect is positive, and captured by $v(x,z)$. Second,

[34] An analogy with classical mechanics once again helps with the notation. Define $\tau = T(x) - T(y)$, so that $d\tau = {}^{dy}/_{i(y,z)}$. From our discussion on expected completion times, we can interpret $d\tau$ as how long it takes to install dy units of capital when we are optimally installing capital at a rate $i(y,z)$. Note that $\tau = 0$ corresponds to stage x. And given optimal investment, can define the stage y where the project will be in τ periods as $\dot{y}(\tau) = i(y(\tau), z)$, where $y(0) = x$. Without defying any laws of physics, we have just renormalized space and time. Suppose we start counting time when the project is at stage x, and normalize that instant to $\tau = 0$. The project will be in stage $y(\tau)$ after τ periods. How quickly does it get there? At an optimum, the velocity of completion is given by $i(y(\tau), z)$ at each point $y(\tau)$.

there is a negative effect arising from revaluing future cash flows at the higher discount rate. This is standard asset pricing: as discount rates rise, project values fall. The following corollary shows that the latter effect becomes negligible as projects approach completion.

Corollary 4. *For x sufficiently close to $\bar{x}$, $\hat{i}(x,z) > 0$.*

Proof. Note that $\hat{v}(x,z)$ becomes arbitrarily small as x approaches $\bar{x}$, as it is the integral of a bounded function over a vanishingly small interval (i.e. $\lim_{x\to\bar{x}} T(x) = 0$). In turn, $v(x,z)$ approaches $pz > 0$. Therefore, it follows from (15) that $\hat{i}(x,z)$ must eventually be positive. □

Corollary (4) rationalizes our intensive margin results. For projects close to completion, the firm increases investment following a discount rate shock. The intuition is simple: remaining time to build is small, and a big payoff awaits the firm if it speeds up the project. Equation (15) then shows it is optimal to invest more in the project. For projects with long time to build, the negative effect from large duration dominates, and it might become optimal to slow down the project.[35]

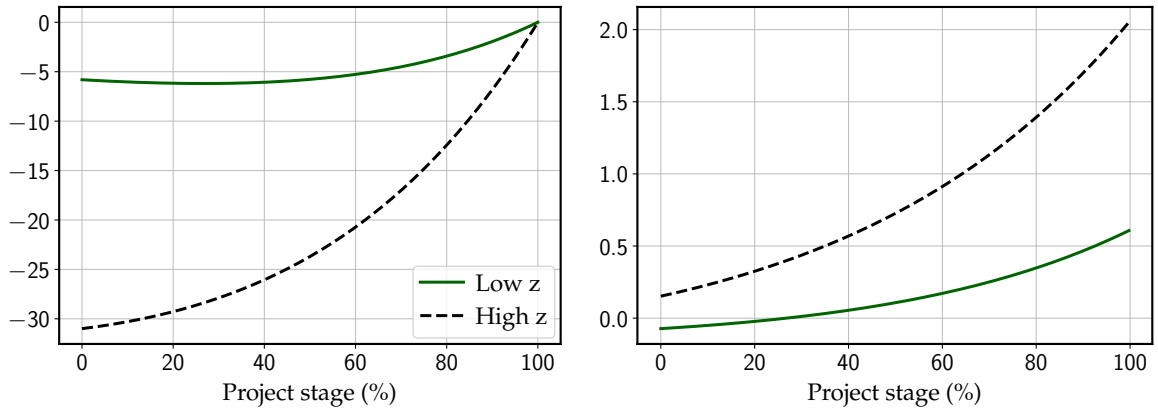
Corollary (4) also qualifies the standard intuition that increases in discount rates necessarily cause investment to fall. At the *project-level*, investment may very well *rise* – a result that upends conventional capital budgeting theory (or, at least, what is taught in MBA programs). How long it takes for the project to yield cash flows matters crucially. This depends on how quickly the firm is building the project; and on how costly it is to accelerate – hence the denominator in (14) and (15). Where the project currently is in its lifecycle (x) summarizes these considerations.

Our results borrow intuition from concepts in fixed income pricing. In Appendix I, we demonstrate that this is not a loose mapping. The underlying economics between accelerating project investments and accelerating bond coupons is quite similar, and reflects a more general insight: changes in the interest rates incentivize agents to shift cash flows (or, more broadly, actions) over time.

Figure 3 illustrates our propositions by showing the impact responses of the value function $\hat{v}(x,z)$ and optimal investment $\hat{i}(x,z)$ to the shock. Panel (a) shows $\hat{v}(x,z)$. Note that it is strictly negative for $x < \bar{x}$, as the payoff upon project completion is more strongly discounted after the shock. In short, all projects fall in value. But project value falls by more for projects that are further away from completion, illustrating the duration intuition of Proposition 2. Panel (b) shows $\hat{i}(x,z)$. For low levels of z, projects are accelerated if they are beyond a threshold stage (around 30-35% of total construction). For high levels of z, it may be optimal to increase investment not only for x close to $\bar{x}$, but even for newly started projects.

[35] In appendix H.3, we extend this result to the case that the firm must operate the project following its completion. p then corresponds to the future value of operating cash flows, which falls as discount rates rise. Even

Figure 3: Responses of the value function and optimal investment to discount rate shock, as functions of project stage



(a) Response of the value function $\hat{v}(x,z)$

(b) Response of optimal investment $\hat{i}(x,z)$

Note: the figure plots the first-order responses of the value function $\hat{v}(x,z)$ (panel a, left) and of the investment policy $\hat{i}(x,z)$ (panel b, right) following a shock to the discount rate. By definition, the y-axis is read as percent-deviations from steady state values. The x-axis is the project stage, defined as $100 \times x/\bar{x}$. Solid green lines represent low output projects ($z = 2$); black dashed lines represent high output projects ($z = 8$). Shock persistence is set at $\rho = 0.17$ and shock size is set at $s = 0.02$, as in appendix table A21. Remaining parameters are set at the same values as in figure 2.

Proposition (3) only speaks to ongoing projects. It qualitatively rationalizes our intensive margin results, but it is silent on extensive margin effects. Our next result addresses this gap.

Proposition 5. *Let*

$$\bar{\mathcal{Z}}(t,s) = \bar{z} + se^{-\rho t}\hat{z} + o(s),$$

where

$$\hat{z} = \left.\frac{\partial \bar{\mathcal{Z}}}{\partial s}\right|_{t,s=0}.$$

The first-order response of the entry threshold $\bar{z}$ to the shock is given by

$$e^{-rT(0,\bar{z})} \times p\hat{z} = -\hat{v}(0,\bar{z}) \tag{16}$$

Proposition (5) states that the change in the threshold follows a standard NPV logic. Given the rise in discount rates, the value of unbegun projects falls by $\hat{v}(0,\bar{z})$. Projects at $\bar{z}$ are no longer positive NPV. To select projects with positive NPV, we need to raise our hurdle by $\hat{z}$. We raise it such that the cash flows $p\hat{z}$ on the marginal projects $(\bar{z}, \bar{z}+\hat{z}]$, once discounted properly, makes up for the lost value $\hat{v}(0,\bar{z})$. To discount cash flows, we use the original discount rate r; and take the time to build of these marginal projects as the relevant

then, we show that so long as cash flows depreciate at a positive rate, it is still optimal to accelerate completion for sufficiently mature projects.

time horizon for receiving the cash flows. Importantly, note that $\hat{z} > 0$, and so the flow of newly started projects decreases after the increase in discount rates, in line with our empirical results (and with standard investment theory).

5 Quantitative Model

So far, we have presented evidence inconsistent with exogenous time to build and shown the theoretical implications of relaxing this assumption for project-level investment. We now enrich the model and bring it to the data. In short, we calibrate the model to the measurements from Sections 2 and Appendix B; and match the estimated elasticities from Section 3.

First, we confront the sizable heterogeneity in project costs and gestation lags. To do so, we let projects be heterogeneous in their sizes $\bar{x}$. We assume project sizes are drawn according to $\log \bar{x} \sim \mathcal{N}\left(\mu_{\bar{x}}, \sigma^2_{\bar{x}}\right)$. We set the parameters of the lognormal distribution to match the 10th, 25th, 50th, 75th, and 90th percentiles of the empirical distribution of log costs. To match the relationship between project size and time to build, we postulate that each project's costless rate of completion $\bar{i}$ depends lon-linearly on project size: $\log \bar{i} \sim \mathcal{N}\left(\beta_0^{\bar{i}} + \beta_1^{\bar{i}} \log \bar{x}, \sigma^2_{\bar{i}}\right)$. Higher draws of $\bar{i}$ for any fixed $\bar{x}$ imply a quicker time to completion (e.g., if time to build was exogenous, a project's (random) time to build would be $\bar{T} = \bar{x}/\bar{i}$). We set the parameters of the $\bar{i}$ distribution to match the average log time to build within each log size quintile. Figure A20a shows our results.

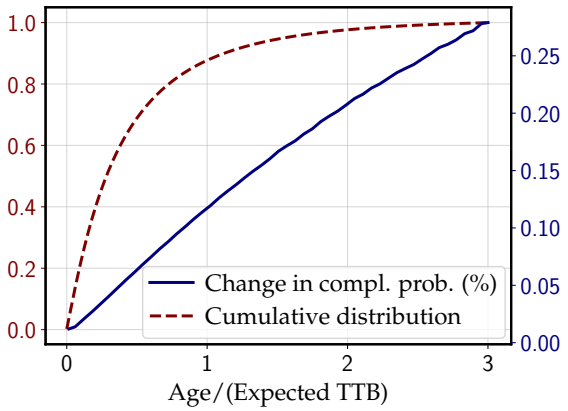
For analytical convenience, we parametrize the distribution of project returns $f(z)$ as a Pareto distribution with minimum draw z_{min} and tail exponent α. We use accounting data on firm revenue to proxy for project gross returns. We trim 1% of the revenue distribution to remove outliers, and run log-rank regressions on the n largest firms following Gabaix and Ibragimov (2011) to obtain the Pareto exponent α. Figure A20b shows our results.

To calibrate the remaining parameters, we use the intensive and extensive margin semi-elasticities $(\beta_{int}, \beta_{ext})$ estimated in columns (5) of Tables 2 and 3. Introducing banks, bank relationships, and banking shocks would significantly increase model complexity, with questionable gains. Instead, following our earlier theoretical results, we map the banking shock to an increase in firm's discount rates. We first estimate ρ by running panel autoregressions of Exposure_{ft} on its first lag, firm, and year fixed effects.[36] Figure A20c shows our results.

We are left with two parameters: the shock size s and the time-to-build endogeneity parameter κ. For any pair of values (s, κ), we can obtain values for the semi-elasticities in the model, so we can set these parameters to match our empirical results using a stan-

[36] To circumvent Nickell (1981) bias, we run a battery of different dynamic panel data estimators: OLS without fixed effects, the Han and Phillips (2010) GMM estimator, and several variations of the system GMM estimators of Arellano and Bover (1995) and Blundell and Bond (1998). Reassuringly, we find similar estimates across all models; and convert them into quarterly figures to arrive at our estimate of ρ.

Figure 4: Heterogeneous Effects in the Model



Notes: the figure plots the cumulative distribution of the proxy stage variable in the model (red dashed line) and the heterogeneous effects of a discount rate shock on hazards by the proxy stage variable (blue solid line). Expected TTB is the cross-sectional average gestation lag across all model projects, i.e. averaging over the joint distribution of $(\bar{x}, \bar{\imath}, z)$. Age is measured in quarters. All parameter values, including shock size and persistence, are as in appendix table A21.

dard minimum distance routine.[37] Though all moments are matched jointly, the intuition for identification is as follows. β_{ext} is uninformative about κ, but informative about s. In turn, β_{int} is informative about both parameters; but β_{ext} and β_{int} move in opposite directions as we change s. The opposing responses to the shock and the differential informativeness of each regression coefficient to κ thus drive identification. Appendix Table A21 collects our calibrated parameters. We estimate a shock size $s = 2\%$, and a acceleration cost $\kappa = 3$. Appendix Table A22 reports that the calibrated model fits well the targeted moments.

As an out-of-sample test, we ask how well the model matches an external moment: the heterogeneous effects regressions. Figure 4 plots the results. The red dashed line plots the cumulative distribution of the proxy stage variable in the model.[38] The blue solid line plots the impact change in completion probability by the proxy stage variable. The effect is a nearly linear function of the proxy stage, consistent with our regression specification. Quantitatively, a unit-increase in proxied stage increases the hazard by 8%. This model-based estimate is not only within the regression's confidence bands, but also completely untargeted in the calibration. We interpret the result as encouraging evidence that data and model speak to each other well when it comes to heterogeneous effects by project stage.

[37] The model-implied semi-elasticities are always computed in partial equilibrium. This is because our regression estimates are informative about partial equilibrium responses: the inclusion of state-by-year and sector-by-year fixed effects absorb effects from changes in local-level prices for construction inputs, sector-level prices for finished or secondary structures, or aggregate-level movements in real rates or factor prices.

[38] We use the unconditional expected time to build in the model. The reason is that the model is minimalist relative to the data. In the model, conditioning on $\bar{\imath}$, $\bar{x}$ or z would strip out most of the variation. In the data, however, the predictive step is much noisier. Even predicting with industry bins, there remains sizable unexplained variation. The unconditional distribution thus provides a better match to the noisy reality of the data.

6 Endogenous Time to Build and Investment Fluctuations

Equipped with our calibrated model, we study the implications of endogenous time-to-build for investment dynamics. Consistent with our earlier theoretical results, we find that increases in discount rates can raise investment. The cross-sectional distribution at the time of the shock determines aggregate dynamics. This strong state-dependence carries implications for the passthrough of monetary policy to investment. In turn, cash flow shocks can drastically alter the timing of investment, thereby carrying implications for the design of investment tax credits. Last, we find that endogenous time to build delivers greater endogenous amplification of structural shocks, generates a measurement wedge between investment expenditures and formation of productive capital away from steady-state, and provides a microfoundation for early investment accelerator theories that emphasized oscillatory dynamics.

6.1 Aggregating Across Projects

To examine the response of investment across projects (i.e., aggregate) to a shock in discount rates (as in our empirical setup), we must first describe how we aggregate across projects. The law of motion for the capital stock K is

$$\dot{K}(t) = I^K(t) - \delta K(t)$$

where instead of accounting investment, the gross increment in productive capacity is given by fixed capital formation $I^K(t)$. We have

$$I^K(t) = \int \underbrace{z}_{\text{capital output}} \cdot \underbrace{g(\overline{x}, z, t) \cdot i(\overline{x}, z, t)}_{\text{flow of finished projects yielding } z \text{ units of capital}} dz$$

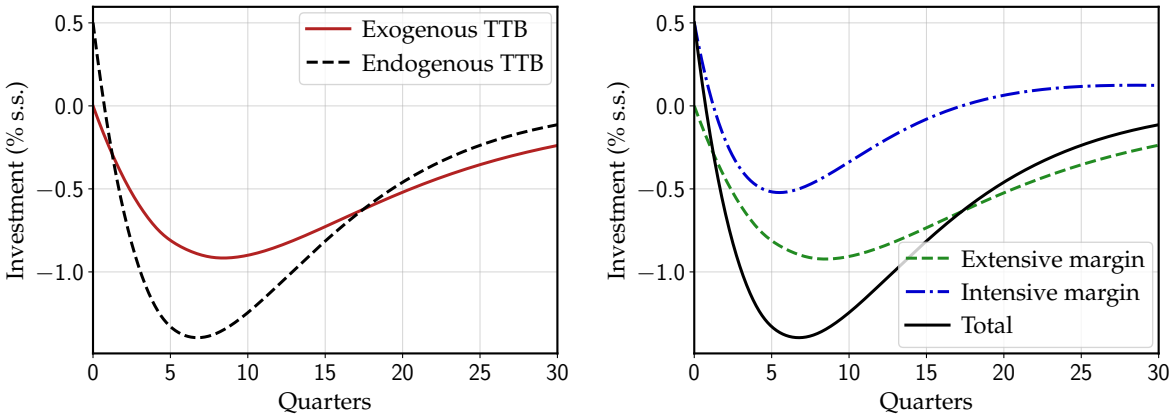
that is, productive capital grows because more projects are completed. Since projects can differ in their output of capital, we aggregate across the distribution of output.[39] Accounting investment, in turn, is given by aggregating investment flows across all ongoing projects

$$I^{acc}(t) = \int \int g(x, z, t) \cdot i(x, z, t) \, dzdx$$

[39] In steady state, equation (11) implies that accounting investment is independent of time to build. In turn, fixed capital formation depends on time to build via its effect on the entry threshold for projects. Formally, letting $M = \int f(z)dz$ be the total mass of entrants, we have $I^{acc}_{ss} = M \cdot \bar{x}$. In turn, since only projects with z above $\bar{z}$ enter, we have

$$I^K_{ss} = \mathbb{E}\left[z | z \geq \bar{z}\right] P(z \geq \bar{z})$$

Figure 5: Impulse response functions of investment to discount rate shock in PE.



(a) Total IRF for endogenous versus exogenous time to build model

(b) Decomposition of endogenous time to build IRF between intensive and extensive margins

Note: the figure plots (quarterly) impulse response functions (IRFs) of aggregate investment to a discount rate shock in partial equilibrium (i.e. fixing p to its steady state level following the shock). The y-axis measures percent-deviations from steady state values. Panel (a) plots the IRFs for the exogenous time to build model (red solid line) and for the endogenous time to build model (black dashed line). Panel (b) decomposes the total IRF (black solid line) from the endogenous time to build model into the extensive margin (green dashed line) and the intensive margin (blue dot-dashed line). Shock persistence, shock size, and remaining parameters as in appendix table A21.

6.2 Amplification and Propagation with Endogenous Time to Build

Figure 5 illustrates our results for a discount rate shock, holding fixed p. We start with partial equilibrium since this assumption is more aligned with our empirical setup. In panel (a), we plot the response of investment when time to build is endogenous (black dashed line) versus exogenous (red solid line, $\kappa \to \infty$). In a world with exogenous time to build, investment falls, reaches a trough 12-16 quarters later, and then returns to steady state, generating a hump-shaped impulse response function (IRF). The dynamics are driven exclusively by entry. Since investment flows are constant conditional on project entry, there is no impact (i.e. time 0) effect on investment. Higher discount rates lower the value of all projects and raise the threshold for a project to be positive NPV. Firms thus start fewer projects today. But fewer projects started today mean lower future investment on ongoing projects. This drives the downward-sloping section of the IRF. Eventually, the discount rate shock starts to revert, and entry starts to return to its normal level. This drives the upward-sloping section of the IRF. Previous theoretical work corroborates this result: to first-order, exogenous TTB is first-order equivalent to investment adjustment costs (Lucca, 2007; Bloesch and Weber, 2023).

In a world with endogenous time to build, investment initially *rises*. The intuition follows from Proposition 3 and Corollary 4. There is a mass of projects close to completion when the shock hits. They are sped up, which leads to an upsurge in investment flows. The extensive

margin component is also present, but is zero at impact. Hence, for the first few quarters, we only have the acceleration effects taking place. The net effect is the short-lived investment spike after the rise in discount rates.

Investment collapses shortly after impact, with intensive margin effects becoming negative. Panel (b) splits the endogenous time to build IRF into an intensive margin IRF and an extensive margin IRF. The former fixes the composition of projects and accounts only for changes in investment rates of ongoing projects; the latter only accounts for entering projects and their subsequent investment flows. To understand the reversal in the intensive margin effects, recall from proposition (3) that while some investments may be sped up, some might be slowed down. As projects close to maturity are completed, the distribution of remaining projects becomes skews towards early-stage projects, for which lower investment is optimal even in steady state – see Figure 2. The distributional change thus drives the drop in investment. The intensive and extensive margins add to each other and generate a steeper fall in investment in the model with endogenous time to build.

Endogenous time to build also delivers oscillatory boom-bust dynamics as ininvestment accelerator theories (Kalecki, 1935; Samuelson, 1939). While they are hardwired in these earlier models, they are microfounded by optimal investor behavior in our setting. The effect is driven by the intensive margin: investment in ongoing projects quickly booms, shortly collapses, and then oscillates back to steady state.

Given investment is more sensitive to shocks in a world with endogenous time to build, casual intuition suggests it should also be more volatile. That is indeed the case: moving from exogenous to endogenous time to build increases investment volatility by 30%. Endogenous time to build allows models to account for investment volatility not by appealing to volatile or large shocks, but rather by generating endogenous amplification. The following proposition provides a lens to interpret the increased responsiveness:

Proposition 6. *Fix any $z > \bar{z}$. For a sufficiently small and temporary shock, the cumulative effect on the intensive margin of investment is zero.*

Proposition (6) shows that the intensive margin IRF has no cumulative effects. The statement is quite general: it holds for any shock, so long as the disturbance does not prevent the distribution from returning to its steady state. Endogenous time to build allows firms to reshuffle investment flows over time. It adds time series variation around a null cumulative effect. Therein lies the source of higher volatility.

6.3 Amplification and Propagation in General Equilibrium

We now show that general equilibrium forces do not undo our partial equilibrium results.

GE Setup. Given a capital stock $K(t)$, we assume that final goods are produced according to

$$Y(t) = A(t)K(t)^{\alpha}$$

where $\alpha \in (0, 1]$ indexes returns to scale, and $A(t)$ stands for stochastic productivity. The price of the final good is normalized to one. The final goods producer buys the aggregate capital bundle $K(t)$ in competitive markets from the capital goods producers, which we have studied throughout the paper so far. Assuming that costs of construction are rebated to consumers, the aggregate resource constraint is

$$Y(t) = C(t) + I^{acc}(t)$$

where $C(t)$ is household consumption. We assume a representative household has isoelastic preferences over consumption $C(t)$, with (inverse) elasticity of intertemporal substitution σ and discount factor ρ.

Standard profit maximization by final goods producers determines capital prices, which reflect future marginal products of capital

$$p(t) = \int_0^{\infty} e^{-\int_0^s (r^f(t+u)+\delta)du} MPK(t+s)ds$$

where $MPK(t) = \alpha A(t)K(t)^{\alpha-1}$ and r^f is the discount rate of final goods producers. When $\alpha = 1$, production of final goods features constant returns to scale, so any partial equilibrium analysis taking as given a price sequence can be recast as a general equilibrium analysis with a particular path of productivity disturbances $A(t)$. When $\alpha < 1$, production of final goods incurs decreasing returns to scale. As more capital is built, the marginal product of capital falls. Capital prices drop, and so does investment. Hence, general equilibrium forces dampen partial equilibrium responses under decreasing returns.

The structure above suffices to endogenize capital prices and understand the joint behavior of returns on capital and investment in industry models (Kalouptsidi 2014, Greenwood and Hanson 2014). In macroeconomic models, further assumptions are needed to pin down discount rates $r(t)$. Standard specifications of household preferences tend to undo the partial equilibrium responses of investment to shocks in general equilibrium.[40] Winberry (2021) adds consumption habits to ensure interest rates are not too sensititve to consumption. We pursue a route that better aligns with our empirical setup by differentiating discount rates of

[40] See House (2014) and Koby and Wolf (2020). The intuition is that changes in investment shift consumption thought the resource constraint, which then shifts interest rates through the consumption smoothing motive of households. The increase in interest rates due to a steeper consumption path mutes the semi-elasticity of investment to a range of shocks.

capital producers and final goods producers.

To be precise, after any MIT shock, final goods producers discount future profits according to the stochastic discount factor

$$M^f(t) = e^{-\rho t}\left(\frac{C(t)}{C}\right)^{-\sigma}$$

where C is steady state consumption. Capital goods producers in turn are subject to a discount rate shock $\varepsilon(t)$, so that their SDF is

$$M^c(t) = e^{-\int_0^t(\rho+\varepsilon(u))du}\left(\frac{C(t)}{C}\right)^{-\sigma}$$

To keep the same notation as before, let $r^f(t)$ and $r^c(t)$ be the discount rate of final and capital goods producers, respectively. We then have[41]

$$r^f(t) = \rho + \sigma\frac{\frac{d}{dt}C(t)}{C(t)} \tag{17}$$

$$r^c(t) = r^f(t) + \varepsilon(t) \tag{18}$$

The key insight is that we can simultaneously shock discount rates of capital producers while allowing GE forces to operate via the usual term $\sigma\frac{\frac{d}{dt}C(t)}{C(t)}$. We interepret $\varepsilon(t)$ as banks deciding to charge higher rates when lending to capital producers. This "spread" shock could be microfounded, for example, by a range of macro-financial models where a banking block is explicitly spelled out, e.g. Gertler and Karadi (2011). The key idea is that some form of market incompleteness (e.g. market segmentation or overlapping generations of bankers without perfect annuity markets) does not allow required rates of return by banks and households to be equalized, leading to a "credit spread" in the economy. This spread is exogenous, but riskless rates of return are endogenously determined by household consumption. With this setup, we can spell out how capital prices and interest rates respond in GE:

Proposition 7. *Let hatted variables denote linearized deviations from steady state. Suppose we announce paths $\hat{A}(t)$ and $\hat{\varepsilon}(t)$ for aggregate productivity and discount rate shocks. Then, to first-order, the response of capital prices is given by*

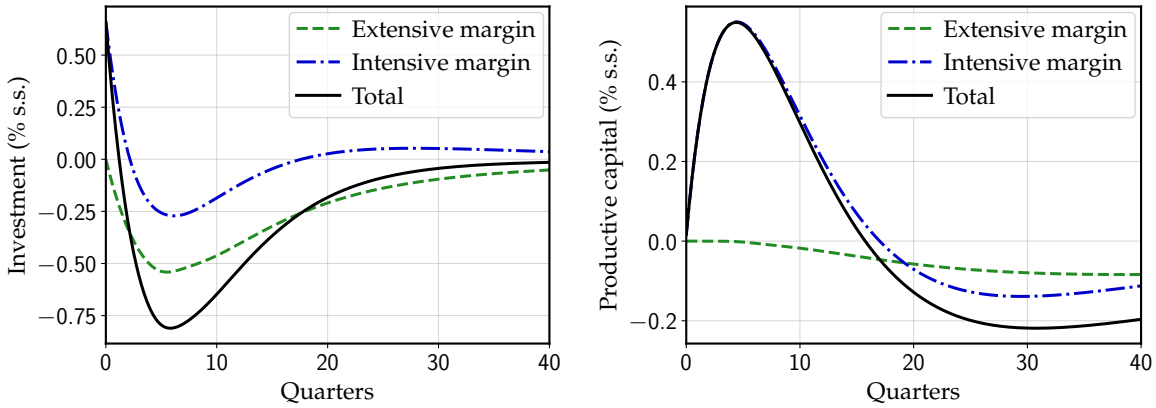
$$\frac{\hat{p}(t)}{p} = (r^f+\delta)\int_0^\infty e^{-(r^r+\delta)s}\left[\frac{\hat{A}(t+s)}{A} - (1-\alpha)\frac{\hat{K}(t+s)}{K} - \frac{\hat{r}^f(t+s)}{r^f+\delta}\right]ds \tag{19}$$

[41] This follows by defining the discount rate that matches the SDF $e^{-\rho t}\left(\frac{C(t)}{C}\right)^{-\sigma} = e^{-\int_0^t r^f(u)du}$, consistent with standard asset pricing.

Proposition 7 highlights three channels by which fluctuations in productivity and discount rates change capital prices. First, there is the direct effect of productivity shocks on the marginal product of capital. When capital is more productive, final goods producers are willing to pay more for it, raising $p(t)$. Second, as productivity or discount rates change, firms revise their investment, thereby altering future capital stocks $\hat{K}(t+s)/K$. Third, there is a direct effect of interest rate changes on the discounting of future marginal products of capital, again holding fixed future paths for the capital stock. As interest rates rise, future marginal products of capital are discounted more heavily, lowering $p(t)$.

Figure 6 shows the response of a discount rate shock $\hat{\varepsilon}(t)$ to capital producers, holding productivity fixed (i.e., $\hat{A} = 0$). First, there is an effect on capital stocks. Capital producers increase investment as they rush to complete project close to completion. This pushes down the price of capital, lowering incentives to invest. Expectedly, the IRF magnitudes are smaller in GE. Regardless, the key results from Figure 5 – the short-run investment spike, the oscillatory dynamics, the endogenous amplification – all survive in general equilibrium.

Figure 6: IRFs of investment and capital to discount rate shock in GE.



(a) Decomposition of investment IRF between intensive and extensive margins

(b) Decomposition of capital IRF between intensive and extensive margins

Note: the figure plots (quarterly) impulse response functions (IRFs) of aggregate investment and the capital stock to a shock in discount rates in general equilibrium. The y-axis measures percent-deviations from steady state values. Panels (a) and (b) plot the IRFs for investment and productive capital, respectively. The total IRF (black solid line) from the endogenous time to build model is decomposed into the extensive margin (green dashed line) and the intensive margin (blue dot-dashed line). Shock persistence, shock size, and remaining parameters as in appendix table A21.

6.4 Tax Policy: Reshuffling Investment over Time

Investment tax credits are a widely used policy lever in recessions. They primarily spur investment by creating a tax shield, effectively generating a positive cash flow shock relative

to the counterfactual world in which the tax credit had not been in place.[42] But when time to build is endogenous, investment responses to cash flow shocks depend not only on whether projects are close or far from completion; but also on the time profile of the shocks. Motivated by these observations, we study the effects of introducing an unanticipated investment tax credit. Firms know once the policy is in place that it will last for 10 quarters. Figure 7 shows the resulting IRFs of accounting investment and productive capital.

In panel (a), the green dashed line plots the IRF of accounting investment in the exogenous time to build model (i.e., the extensive margin of the endogenous time to build model). The positive cash flow shock induces project entry. Investment slowly rises as firms build nascent projects. As the tax credit expires, investment starts to returns to steady state. The long-lived effects of the shock result from distributional dynamics: since projects were started, the IRF accounts for cash flows that will be spent on these projects, even after the tax credit is long gone. Only as they are completed, investment returns to steady state.

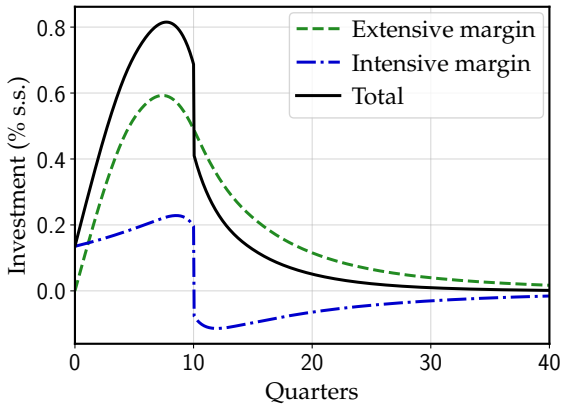
The blue dashed line turns to the endogenous time to build effect. The striking feature of the IRF is its shape: investment rises on impact, keeps rising, but then collapses at the time that the credit expires, and then reverts to steady state. The intensive margin effectively allows firms to reshuffle investment over time. It is entirely responsible for the impact effect: investment flows rise for all ongoing project as firms front-load investment to periods when it's cheaper to build. The intensive margin slump in turn reflects distributional dynamics. Though investment rises for projects across the stage distribution, more mature projects respond by more. As projects are completed, the distribution skews towards younger projects. It is optimal to invest less in these projects – even in steady state. When the credit expires, the distribution is skewed towards younger projects, resulting in the bust. As these projects age, investment flows pick up, and the aggregate impulse returns to steady state.

Panel (b) show the productive capital IRF. It accumulates more quickly in the endogenous case, which reflects the front-loading of investment flows, particularly so for projects that are closer to completion. Last, panels (c) and (d) repeat the exercise in general equilibrium. Consistent with our findings on discount rate shocks, we find that general equilbrium forces do not undo the partial equilibrium effects, but dampen the responses.

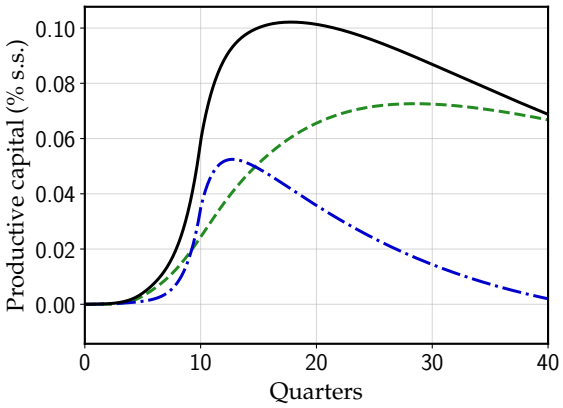
The investment IRFs highlight our first policy takeaway. The cumulative response of investment to tax credits comes from project starts. To first order, temporary tax credits just imply an intertemporal reshuffling of expenditures. This is not to say that investment tax credits are useless. Quite on the contrary, our results suggest they provide incredible flexibility to policymakers. If aggregate demand is currently low, we can spur investment

[42] For illustration, Appendix Figure A22 shows the effect of a (perfect foresight) AR(1) shock to p (i.e., a "cash flow" shock). When terminal payoffs rise, firms rush to complete projects, spurring an investment spike driven by both ongoing and newly-started projects. Investment tax credits usually operate by lowering costs rather than increasing terminal payoffs, but the exercise clearly illustrates how higher cash flows induce acceleration and thus higher investment.

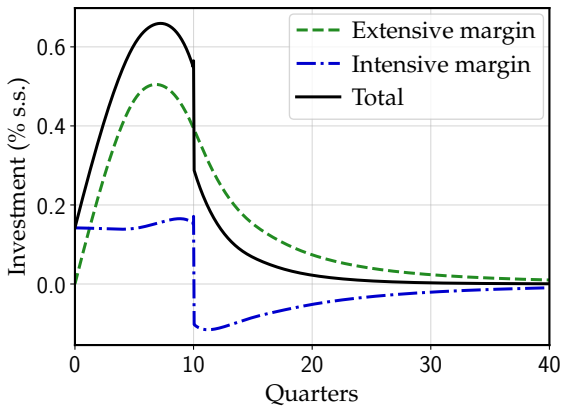
Figure 7: Endogenous Time to Build and Investment Tax Credits



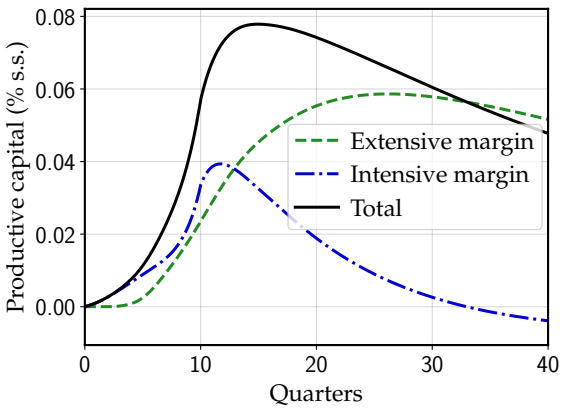
(a) IRF Decomposition: I^{acc} (Partial Equilibrium)



(b) IRF Decomposition: K (Partial Equilibrium)



(c) IRF Decomposition: I^{acc} (General Equilibrium)



(d) IRF Decomposition: K (General Equilibrium)

Note: the figure plots (quarterly) impulse response functions (IRFs) of aggregate investment (panels a and c) and aggregate capital stock (panels b and d) to the (unanticipated) introduction of an investment tax credit at $t = 0$ lasting for 10 quarters. The y-axis measures percent-deviations from steady state values. Panels a and b show partial equilibrium responses. The black dashed line captures the total IRF; the green dashed line plots the extensive margin component of the IRF (i.e. fixing investment policies to steady state levels, but allowing entry to respond to the shock); and the blue dot-dashed line plots the intensive margin component of the IRF (i.e. shutting down entry, but allowing investment rates to respond to the shock). Panels c and d repeat the exercises in panels c and d, but allowing for general equilibrium responses. Remaining parameters are as in appendix table A21.

today by borrowing it from the future. The duration and the size of the tax credit provide two levers for policy makers to intertemporally reshuffle aggregate demand.

Our second policy takeaway is that investment tax credits are a particularly flexible tool to spur investment relative to monetary policy. While changes in discount rates affect the entire path of cash flows accruing to a project, changes in tax policy can more flexibly target the "short-end" of the cash flow curve relative to the "long-end".[43] Fiscal policy does share one commonality with monetary policy: its effects are state-dependent. If the distribution of projects had been skewed towards later-stage projects when the investment tax credit was introduced, we would have observed stronger intertemporal reshuffling of investment flows and therefore a stronger short-term investment boom. Conversely, had the distribution been skewed towards earlier stage projects, the aggregate effects would have been muted.

We have mostly focused on investment tax credits as a tool for stabilization policy. Investment subsidies can speed up structural change. The Inflation Reduction Act and the CHIPS Act of 2022 had explicit rationales linked to accelerating the green transition and the reshoring of strategic industries, respectively. Our model clarifies how these policies trade-off speed gains with acceleration costs; and provides a portable framework to quantify such costs and benefits. This is a promising application for future research.

6.5 State-Dependence

Recall from Figure 4 that the effects of a discount rate shock on investment flows are heterogeneous. Projects that are closer to (farther from) completion are sped up (slowed down) – a central model prediction that is borne out in the data. Consequently, the distribution of projects at the time of the shock determines the aggregate effect. What if the economy had recently experienced an influx of new projects? Or what if the economy had been recovering from a period of sluggish starts, with the distribution being skewed towards older projects?

Figure 8 studies these settings. We operate in partial equilibrium to isolate the theoretical channel. In Panel (a), we plot three distributions of projects over stages. The first is the steady state distribution (black solid line, Figure 5). We then consider two alternative scenarios. In the first, the economy has experienced a sharp influx of new projects, skewing the distribution towards less mature projects (green dashed line). In the second, the economy instead has experienced a prolonged period of no starts, so the distribution skews towards old projects (blue dot-dashed line).

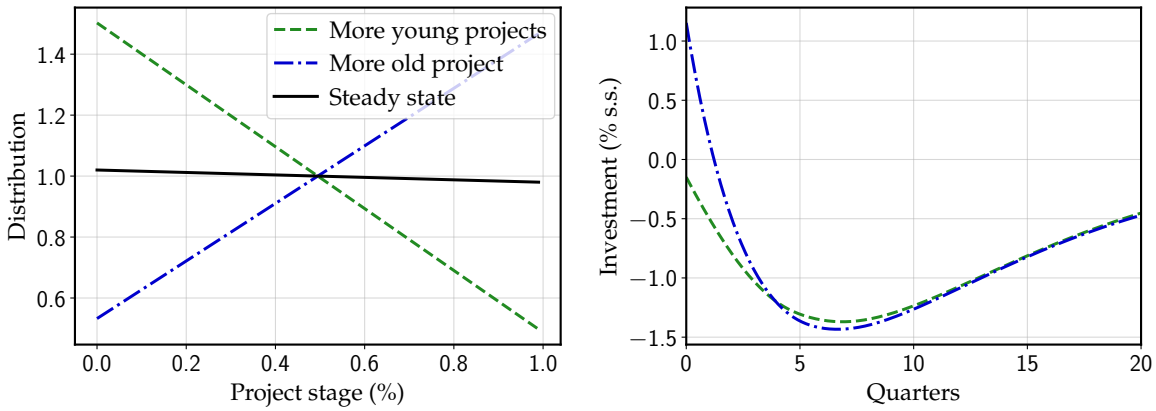
Panel (b) plots the response of aggregate investment to the discount rate shock of Figure 5, but starting from each of the skewed distributions. When the economy starts filled with mature projects, the initial investment spike is larger. In turn, when the economy starts filled

[43] While q-theory models with convex adjustment costs (Hayashi, 1982) can also generate our first policy takeaway, they cannot generate this second implication.

with fledgling projects, the impact response turns negative. The distributional dependence is so strong that the effect on impact can even flip signs depending on initial conditions.[44]

Figure 8 carries lessons for monetary policy. The effects of interest rate changes on investment are state-dependent – an effect also documented in the context of mortgage refinancing (Berger et al., 2021; Eichenbaum et al., 2022) and durables purchases (McKay and Wieland, 2021). Interest rate hikes (cuts) will be less contractionary (expansionary) on impact when the distribution is skewed towards more mature projects. In short, the investment channel of monetary policy may face headwinds that are absent when time to build is exogenous.

Figure 8: Endogenous Time to Build and State-Dependent Monetary Policy



(a) Distributions of Projects Across Stages

(b) Investment IRF to r Shock Across Different Starting Distributions

Note: the figure illustrates the state-dependent effects of monetary policy in a world of endogenous time to build. Panel (a) plots the steady state distribution (black solid line), and two "counterfactual" distributions at the time of the shock: one skewed towards younger projects (green dashed line), and one skewed towards older projects (blue dot-dashed line). Panel (b) plots (quarterly) impulse response functions (IRFs) of aggregate investment to a discount rate shock in partial equilibrium (i.e. fixing p to its steady state level following the shock). The y-axis measures percent-deviations from steady state values. The green dashed line plots the IRF when the distribution is skewed towards younger projects at the time of the shock. The blue dot-dashed line plots the IRF when the distribution is skewed towards older projects at the time to the shock. The IRF for the steady state distribution is the black dashed line in Panel (a) of Figure 5. Shock persistence, shock size, and remaining parameters as in appendix table A21.

[44]One may ask whether the distribution of projects along stages varies over time in the data. Unfortunately, as project stages are unobserved, so is such distribution. In unreported results, we explored a proxy "distribution", where we isolate completed projects, compute the time since each start, and normalize it by the total time to build so it lies between 0 and 1. We plot its distribution across five-years intervals and find evidence on time-variation. But admittedly this distribution suffers from selection bias and could incorporate compositional changes in types of projects, so this evidence is only suggestive.

7 Conclusion

Leveraging detailed project histories of large capital expenditure projects in India, we have shown that time to build is a pervasive microeconomic feature of fixed capital formation across industries, sponsor types, time periods, and project sizes. We provided causal evidence that firms have control over project timelines; and rationalized our findings in a neoclassical investment model with a single new twist: endogenous time to build. We showed that this endogeneity has distinctive implications for the economics of investment and capital formation, both in partial and general equilibrium. Investment becomes more responsive to shocks, and thereby more volatile. More mature projects react more strongly relative to fledgling projects – a key model prediction that is borne out in the data. As a result, the distribution of projects along their completion lifecycle shapes aggregate dynamics. Monetary policy becomes state-dependent: the distribution of projects at the time of the interest rate change determines impact effects. The implications are not restricted to discount rate shocks. Investment in ongoing projects is extremely responsive to variations in cash flows, opening up space for time-varying investment credits to flexibly reshuffle aggregate demand across expansions and recessions; and suggesting novel roles for investment subsidies as structural policies to accelerate infrastructure development, such as the green transition.

Data at more disaggregated levels (e.g. project- or structure-level data) allows for further measurement and thereby better microfounded models of capital formation. We have provided a minimal setup that captures key economic forces, but is portable to other settings (e.g., managing a collection of workers or tasks) and invites extensions (e.g., asymmetric information). But there is more to build, and questions are not in short supply. Take for instance the buildup in data centers and energy facilities within the artificial intelligence value chain. Do firms internalize gestation lags of their competitors when expanding capacity, and how does that shape industry dynamics and competition? More broadly, can we structure project financing practices that internalize the resulting incentive effects in gestation lags? Do short-termist politicians speed up project and overrun budgets to claim credit for successful completion before their tenure ends, and can such incentives explain the political investment cycles? How much can targeted subsidies speed up infrastructure development in laggard economies or a global green transition? Can our insights from fixed capital formation be generalized to breakthrough innovations or other intangible forms of capital? Future research will continue to tease out further implications of endogenous time to build.

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Online Appendix (Not for Publication)

A Data Appendix

A.1 CapexDx

We provide additional information on data collection, definitions, and limitations for our project-level data.

A.1.1 Defining Projects

CMIE defines a project when it can assess the capacity that will be created. They illustrate the definition as follows. Suppose a sponsor decides to invest a hundred million rupees in India. This does not constitute a project: we don't know the capacity that is being created (i.e. whether it is a factory, a road, a school building, etc). Suppose further that the sponsor specified that it would invest in the glass industry. Again, it is not clear what capacity is being created. Is it a factory to produce glass? Or is it a warehouse to store glass? Perhaps it could be a new headquarter building for the sponsor.

Suppose then that the conglomerate specifies that it will invest a hundred million rupees in a glass manufacturing plant in Chennai. Now, there is clarity on the capacity that will be created. To quote the documentation, "Although the company has not categorically stated so, it does imply the creation of additional capacity, unless the context or circumstances suggest otherwise." CMIE therefore tracks the project. Importantly, CMIE would not track the project if the sponsor was just acquiring an already existing glass manufacturing plant, rather than developing the structure.

Some projects are multi-faceted and complex. They might combine several smaller projects. In that case, CMIE recognizes "the smaller logical components as independent projects if the cost for each of them is available separately and if the implementation is clearly separate". Consider the glass manufacturing example above. If the sponsor specified that there would be four plants in the complex, each costing 25 million rupees, with plants being simultaneously built and with equal capacity, then CMIE would track each plant individually. The exception would be if the sponsor explicitly states that it considers all sub-components of the larger project as a single, integrated structure. CMIE then follows the sponsor and defines a single project, despite detailed information on sub-components. In that case, or in the absence of such granular information on project sub-components, we would observe our example in the data as "Glass Manufacturing Project" with a total cost of 100 rupees located in Chennai.

A.1.2 Data Collection

CMIE builds Capex by combing publicly available sources and by actively contacting sponsors via emails and phone calls. This detective work reflects the lack of systematic sources of project-level data. There is no universal standard of disclosure that sponsors must follow, either in company reports (i.e. disclosures of materially relevant information for investors in the case of public companies) or in government forms. CMIE therefore collects the data from any and all credible sources.

To quote CMIE, their "long experience in building and maintaining such a database and in applying it in its own research ensures the utility of the database." Indeed, many players in industry, government and academia rely on CMIE products to obtain reliable data on the Indian economy. Capex is no exception. Practitioners we spoke to suggest they actively used Capex to either track existing projects or make strategic decisions regarding future capacity creation.

Our conversations with the data provider further alleviates data quality concerns. First, monitoring is regular, as all projects "are touched for updates once in a quarter." Second, CMIE recognizes the need to validate sponsor information. To quote a conversation we had with the Capex team: "Media, government websites are also source of capturing of events that measure the progress of implementation of the project. If these are the sources of information then we do not rely for the company to disclose the same progress." Third, CMIE actively checks for outdated information in their tracking. Suppose CMIE learns after contacting promoters that implementation for a particular project happened one month before what CMIE had as the original implementation start date. In that case, CMIE checks the veracity of the sponsors' claims against other sources it has used previously, such as public disclosures by government sources or media outlets. If CMIE finds corroborating evidence in the public domain for the sponsors' claims, it then updates the outdated information to the most recent news.

Dating of events reflects data collection. In many cases, the date of an event is the date when the information was available to CMIE. For example, announcement dates correspond to the first time that the project is mentioned in the public domain; implementation start dates mark the first time that CMIE learns that an implementation-related event has taken place, either from public domain sources or from project sponsors.

Despite intense monitoring, CMIE may fail to follow a project's full history. While we observe announcement dates for all projects, we do not always know what eventually happened to a project. In short, some observations are right-censored. We deal with this feature of the data in two different ways. In some exercises, we restrict analyses to non-censored projects or exclusively to completed projects. In the parlor of survival analyses, we perform "complete case" analyses, aware we cannot circumvent sample selection concerns depend-

ing on our outcome of interest. In other exercises, we leverage econometric methods that take into account the right-censored nature of the data, thereby allowing us to maximize the number of observations we can learn from.

Reassuringly, we understand part of the data generating process for censoring — at least that under the discretion of CMIE. CapexDx discloses it stops tracking projects "if they are stalled or shelved or abandoned or information regarding them is not available for over 30 months in the case of manufacturing projects and for over 36 months in the case of infrastructure projects." Right-censoring is not a one-way street: CMIE resumes tracking previously censored projects if it manages to obtain reliable information on project status from the public domain. In short, the combination of intense monitoring and transparent censoring schemes bolsters data reliability.

A.1.3 Raw Data Structure

Before we start describing how we construct event histories for our econometric exercises, it is convenient to describe the individual files we start from. All such files can be obtained with a subscription to CapexDx. We use the March 31st 2023 vintage for our analyses.

- Project Detail file: cross-sectional data on project characteristics, such as project name and id, sponsor name and id, state and district of project, most recent project status, etc.
- Project Costs file: data at the project-cost estimate level, including date of cost estimate. Projects may have multiple cost estimates over their lifetime, which we refer to as "restatements".
- Project Completion file: cross-sectional data for completed projects, specifying dates of completion and previous estimates of completion dates.
- Project Events file: data at the project-event-event date level, tracks project lifecycle.

A.2 Constructing Event Histories

The ability to track events at the project-level is a noteworthy feature of CapexDx. However, pre-processing is required before any meaningful econometric analysis can be carried out. This is mostly because of the structure of the raw data: the event histories contain an "event" for each row. This means that multiple events can happen in the same date, which is often the case.[45] For running our hazard models, however, we must construct a panel at the project-calendar time level.

[45]For instance, there might be three entries in a particular date – (i) sponsor contacted successfully, (ii) construction commenced, and (iii) foundation stone laid. Event (i) is informative that the project is being actively monitored, but does not provide us any information about the project's ongoing construction. It is simply an

We therefore reduce the dimensionality of the event-level data. Our strategy is to use the event-level data to construct a project-level panel that tracks whether the project is in one of the following stages: announced, shelved, stalled, under implementation, completed, abandoned, or lost to follow-up. These correspond to the labels used for project statuses in the Project Detail file.[46] Completion, abandonment/shelving, and lost to follow-up are terminal (or, absorbing) stages. All remaining stages correspond to "intermediate stages", from which a project may transition in or out from. For example, though all projects start as "announced", a project might temporarily move into "stalled", then back into "announced", and then become "under implementation".[47]

Below we describe the criteria we use to characterize a project over time in each one of these stages. We implement each step sequentially, carefully browsing and visualizing the data as we implement each step, and recurrently checking individual project histories to ensure accuracy. We start with the terminal stages:

- *Completed*: any event date that occurs at or after we observe one of the events "Completed" or "Commercial Production". In cases when "Completed" or "Commercial Production" both appear in the event history but do not share the same event date, consider last event as marking completion. The project is marked as "Completed" in the Detail file.

- *Abandoned (Shelved):* any event date that occurs at or after we observe the event "Abandoned on" ("Shelved on").[48] The project is marked as "Abandoned" in the Detail file.

- *Lost to Follow-Up:*

informational marker. Events (ii) and (iii), however, provide critical information on the project's lifecycle. We learn that the project moved into implementation.

[46]Sadly, CapexDx does not have a variable keeping track of these stages over time in the event file, which would have made our wrangling much easier. The stage variable in the detail file corresponds only to the most recent project stage as of the vintage release.

[47]We first do some pre-processing of the events data to simplify our wrangling. First, we drop some events that are not informative for our purposes. Many events in the data are "Company contacted successfully" or "Company contacted but no response". These events are can be used to measure the intensity at which CapexDx tracks a project, but do not convey any information about the project by themselves. We first remove these rows from the events dataset and manipulate them in a separate dataset to obtain monitoring intensity measures. To be precise, we drop such events if either (1) there is another event in the same date that is not a monitoring marker, or (2) they occur by themselves, but are neither the first or last event in the project's history; or if (3) they are the last observations in the project history, but the preceding event in the project history is either completion, abandonment, or shelving. Second, some projects feature multiple subprojects or phases. Some events relate to particular phases (often marked by containing the substring "for pr/s/u/ph" in the event description). We remove these events as CapexDx also creates event markers that apply to the entire project.

[48]In a minuscule number of cases, the project flows in and out of abandonment or shelving. We contacted CMIE to inquire about these cases. Indeed, these are project where ex-post CMIE acquired information that the project sponsor reversed the decision and continued implementation of the project. In these cases, we treat abandonment as an intermediate rather than terminal stage. Our results are not sensitive to including or not such projects.

- If there is only one event “No information as on” throughout the event history: any event date that occurs at or after we observe such event. The project must be marked as “No Information” in the Detail file.
- If there is more than one event “No information as on” throughout the event history: periods of temporary loss to follow-up can be identified by the initial events “No Information as on” and the terminal events “No information as up to”. For the purposes of understanding completion dynamics, we are not interested in "No information" as a time-varying state. If this "no information" will be succeeded by some other event, we take the last-occurring “No Information as on” marker as when the project becomes censored; and assume that whatever state the project was in before this no information period is the state in which the project remained during this period.[49]

For the remaining stages, a project may transition in and out of a particular stage. We thus have to keep track not only of markers indicative of entry, but also of markers indicative of exit.

- *Stalled:* a project is marked as stalled during the following time periods:
  - Event dates between the entry event “Implementation stalled on” and the exit event “Stalled up to” or any exit events marking transition into a terminal stage (abandonment, completion, loss to follow-up, or shelving).[50]
  - Event dates between the entry event “Announced and stalled on” and the exit event “Stalled up to” or any exit events marking transition into a terminal stage (abandonment, loss to follow-up, or shelving).[51]
  - Event dates starting at the entry event “Implementation stalled on” or “Announced and stalled on”, but without a transition into a terminal stage. For such cases, we manually check the histories of each project. These histories normally feature many monitoring markers such as “Company contacted successfully” or “Company contacted but no response”, or are the last entries in a project’s event history. These projects are more recent and still in active stallment.

[49] Granted, this not deal with potential cases where the "no information" period is a period where the project went through a different state (e.g. if it was temporarily stalled during this non-information spell, but the data provider could not obtain such information). However, we cannot circumvent this non-observability; and, except for analyzing transition matrices, this data decision will not influence our results.

[50] There are 16 projects in the entire dataset that move from stallment from completion. We cannot disambiguate whether this means the project was completed to begin with, but its operations were put on hold, or whether the data provider was unable to ascertain at which date implementation resumed.

[51] There are no projects in the entire dataset that move from completion after this initial entry event. The marker “Announced and stalled on” is used by the data provider to indicate a project where the first contact with the project occurs at a point where the project is already stalled.

- *Under Implementation:* a project is marked as under implementation during the following time periods:
  - Event dates between the entry event "Implementation started" and the exit event "Implementation stalled on" or any exit events marking transition into a terminal stage (abandonment, completion, loss to follow-up, or shelving).[52]
  - Event dates starting at the entry event "Implementation stalled on" or "Stalled up to", but without a transition into a terminal stage. For such cases, we manually check the histories of each project. These histories normally feature many monitoring markers such as "Company contacted successfully" or "Company contacted but no response", or are the last entries in a project's event history. These projects are more recent and still in active implementation.
- *Announced:* a project is marked as announced during the following time periods:
  - Projects that were never started: event dates between the entry event "Date of Announcement" and the exit events "Announced and stalled on", "Shelved on".
  - Projects that are eventually started: event dates between the entry event "Date of Announcement" and the exit events "Announced and stalled on", "Implementation started", or any exit events marking transition into a terminal stage (abandonment, completion, or loss to follow-up).[53]
  - Very recent projects: event dates between the entry event "Date of Announcement", but without a transition into another stage. For such cases, we manually check the histories of each project. These histories normally feature many monitoring markers such as "Company contacted successfully" or "Company contacted but no response", or are the last entries in a project's event history. These projects are more recent and we simply do not know what will happen to them.

Once we construct these time-varying stages, we ensure the resulting histories are sensible. We implement the following assertion tests:

[52] A project might have more than one "Implementation started" marker. These cases correspond to multiple spells of implementation within a single history, often marked by temporary stallment. In these cases, we mark each spell separately as to adequately capture the multiple spells in the history. In rare cases of multiple implementation spells, the entry event is "Stalled up to", unaccompanied by the "Implementation started" event but with a preceding "Implementation started" event earlier in the project history. For such cases, we manually check the histories of each project.

[53] A project might go through multiple spells of having been announced, but either not having started to be implemented yet (e.g. licenses are being procured), or being temporarily stalled. In these cases, we mark each spell separately as to adequately capture the multiple spells in the history. In rare cases of multiple "announce and hold" spells, the entry event is "Stalled up to", unaccompanied by the "Date of announcement" event but with a preceding "Date of announcement" event earlier in the project history. For such cases, we manually check the histories of each project.

1. At any point in time, a project is assigned to one of the above stages.

2. At any point in time, a project is assigned to a single stage (i.e. a project cannot be simultaneously under implementation and stalled, or completed and lost to follow-up).[54]

At this point, a project's event history is effectively constructed. We now only need to convert the event date-event-project level dataset into a project-time level dataset that can be used for conventional analyses. In a first step, we convert the data to a project-day level data. Then, we aggregate to the quarterly frequency.[55] Last, to estimate transition probabilities and hazard models, it's important for the data to feature a particular structure: the last row should capture the transition into the terminal stage. After doing so, we obtain our final quarterly panel on project histories, to which we can merge any time-varying or cross-sectional information on projects, their sponsors, their geographies, etc.

Note that we could have simply characterized the project as "completed" or "not completed" for the purposes of our main regression exercises. However, we wanted to ensure that the project history was sensible, i.e. indeed transitions across different stages painted a coherent story of the project's lifecycle. This was a key motivation for engaging in the full-scale wrangling exercise and producing Appendix Table A3.

A.2.1 Examples

To illustrate the cleaning procedure, we consider a fictitious project with multiple events. Note that to preserve the raw data integrity of the data provider, this is a fictitious project, merely for illustration of how we can go from raw event-level data to project-level data.

The first example (project ID 1) illustrates a straightforward case: the project is announced, starts implementation, and is eventually completed. In this example, we supress events that are not essential for our classification of time-varying stages (e.g. monitoring events, markers for initial estimates of completion dates, etc) to avoid clutter. For the same reason, we omit columns for stages that are all zeros over the project's lifetime.

[54] In a minuscule number of cases, we find that our procedure produced overlapping stages. We manually disambiguated the event histories in such cases by looking at the entire project history and determining which stage made most sense and whether the entire project history looked sensible.

[55] We compute the number of events per month and per quarter before aggregating, and don't find considerable discrepancies, which alleviates concerns that we are losing key information about the project's history by aggregating. Whenever there are more than two stages in a particular quarter, we follow standard procedure in survival analysis and take the last stage as the stage for the entire quarter. For example, if the project moves from announcement to implementation in the middle of 2011:2, the project is considered "under implementation" for the entirety of 2011:2.

Event-Time Panel

ID	Event	Event Date
1	Date of announcement	05/20/2006
⋮	⋮	⋮
1	Implementation Started	09/02/2007
⋮	⋮	⋮
1	Completed	07/13/2012

→

Project-Time Panel

ID	Calendar	Announced	Under Imp	Completed
1	2006:2	1	0	0
⋮	⋮	⋮	⋮	⋮
1	2007:2	1	0	0
1	2007:3	0	1	0
⋮	⋮	⋮	⋮	⋮
1	2012:2	0	1	0
1	2012:3	0	0	1

The second example illustrates a more nuanced case: the project becomes temporarily stalled, and later on continues to be implemented. However, the project is then stalled again. The data provider fails to obtain more information on the project from the company, and eventually the project is marked as lost to follow-up. This example illustrates how projects may go in and out of particular stages of implementation.

In this example, we include the monitoring markers provided by CapexDx. This serves two purposes. First, it illustrates the intense monitoring efforts of the data provider; second, it illustrates how loss to follow-up occurs when the data provider cannot ascertain what is happening to the project after successive attempts to obtain information on the project status for a given period of time.

Event-Time Panel

ID	Event	Event Date
2	Date of announcement	11/05/2005
2	Contacted Successfully	08/01/2006
⋮	⋮	⋮
2	Land acquired	11/11/2008
2	Implementation started	11/11/2008
2	Contacted Successfully	11/11/2008
⋮	⋮	⋮
2	Implementation stalled on	04/20/2009
2	Contacted Successfully	04/20/2009
⋮	⋮	⋮
2	Stalled up to	04/01/2010
2	Construction commenced	04/01/2010
2	Contacted Successfully	04/01/2010
⋮	⋮	⋮
2	Implementation stalled on	08/21/2012
2	Contacted Successfully	08/21/2012
⋮	⋮	⋮
2	Stalled up to	10/09/2012
2	Contacted Successfully	10/09/2012
⋮	⋮	⋮
2	No response	02/09/2013
2	No response	07/10/2013
2	No response	12/01/2013
2	No response	04/13/2014
2	No information as on	06/27/2014

→

Project-Time Panel

ID	Calendar	Announced	Under Imp	Stalled	No Info
2	2005:4	1	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮
2	2008:3	1	0	0	0
2	2008:4	0	1	0	0
⋮	⋮	⋮	⋮	⋮	⋮
2	2009:1	0	1	0	0
2	2009:2	0	0	1	0
⋮	⋮	⋮	⋮	⋮	⋮
2	2010:1	0	0	1	0
2	2010:2	0	1	0	0
⋮	⋮	⋮	⋮	⋮	⋮
2	2012:2	0	1	0	0
2	2012:3	0	0	1	0
2	2012:4	0	1	0	0
⋮	⋮	⋮	⋮	⋮	⋮
2	2014:1	0	1	0	0
2	2014:2	0	0	0	1

A.3 ProwessDx and Charges Data

We obtain annual and quarterly-level accounting data from ProwessDx, and merge any relevant variables with our project-level dataset at the firm-time level.

We obtain charge-level data from the Ministry of Corporate Affairs. We collect data on

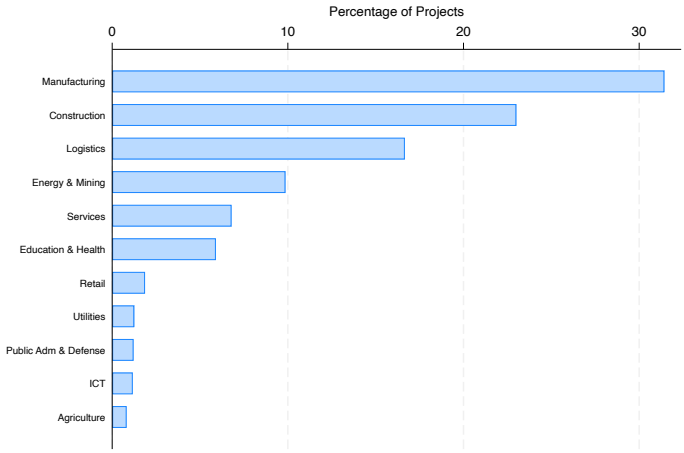
entities whose CIN codes are present in ProwessDx. As described in the main text, we undertake a combination of fuzzy matching algorithms and extensive manual checks to arrive at a cross-walk between the name of the lending entities in the MCA data and the names of companies or banks in ProwessDx. Once we have the names of the lending entities, we can obtain their Prowess company codes to ensure a smooth matching with other data. For the borrowing entities, matching with Prowess data is straightforward since we have their CIN codes in both datasets.

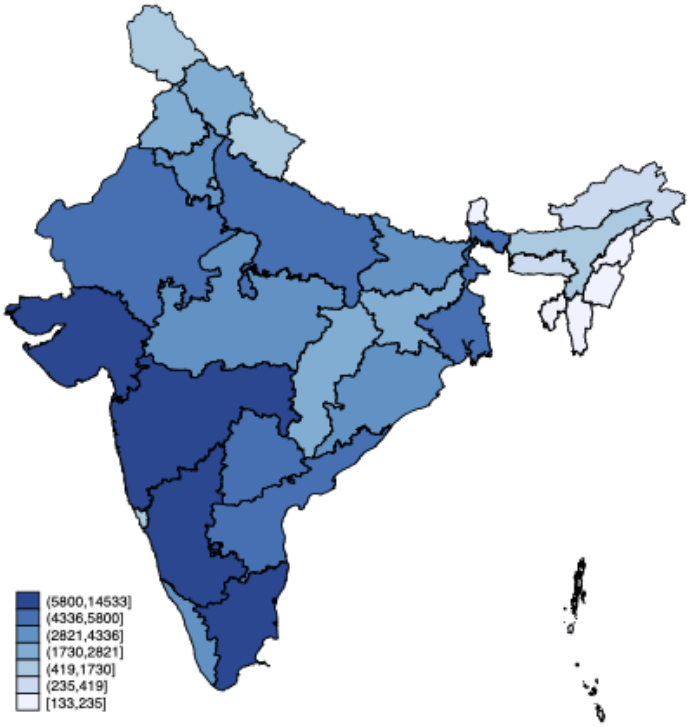
In order to arrive at a bank-firm-time panel, we first expand the data to get a panel at the loan-time level; and then compute any relevant variables (eg. total amount outstanding in an year) at the appropriate bank-firm-time level. To move from a bank-firm-time to a firm-time or a bank-time level dataset, we again compute any relevant variables before collapsing the data. Relative to the project-level dataset, wrangling of these data are more straightforward.

B Additional Measurement Exercises

Figure A0: Project Counts by Sector and Geography

(a) By Sector



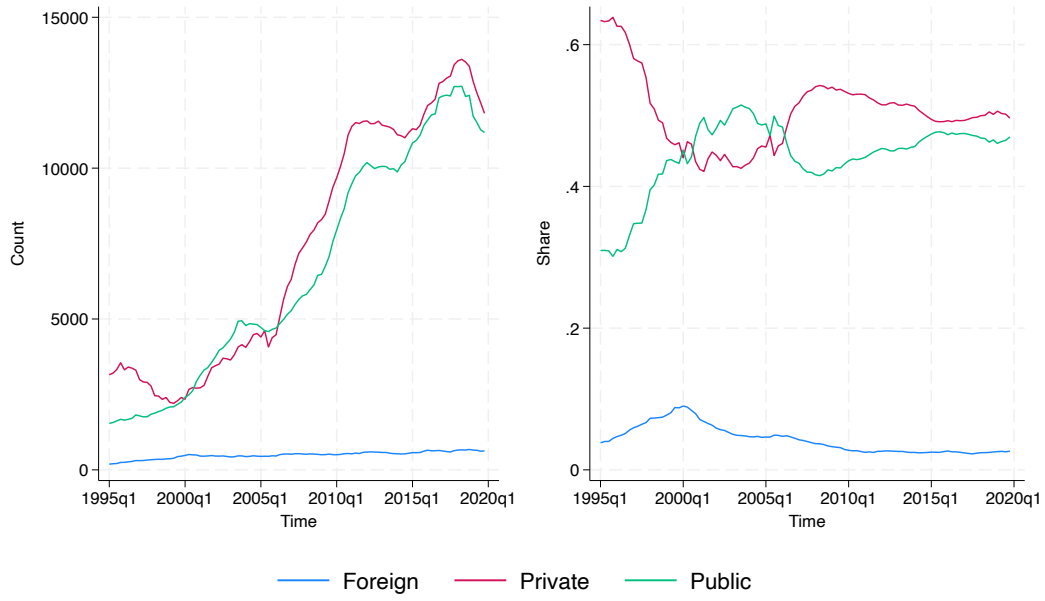


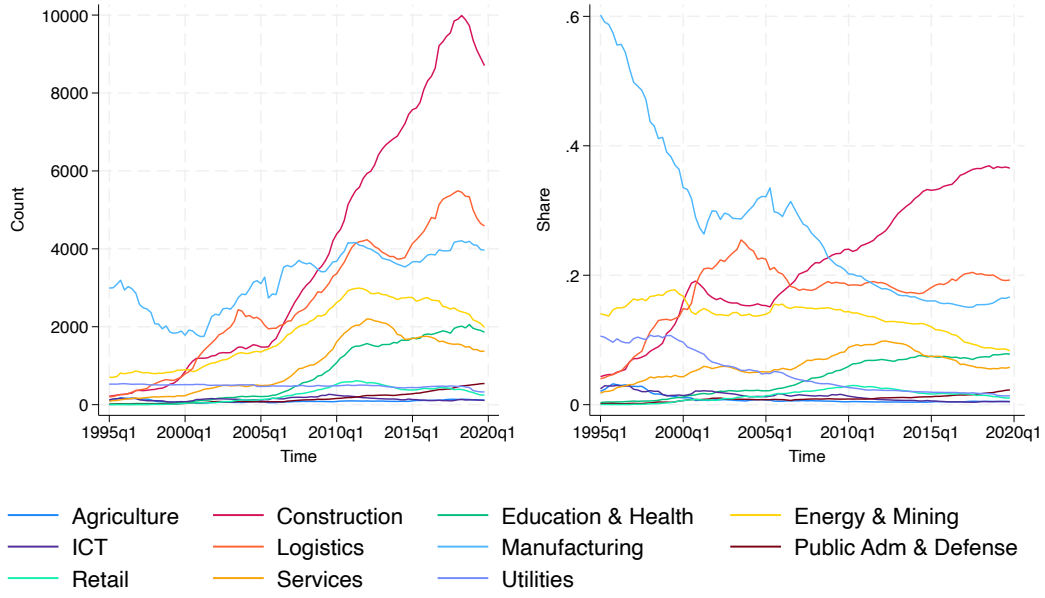
(b) By State

Notes: The figures plot the total number of projects by sector (top panel) and geography (bottom panels) across all years in the data. For visualization purposes, we aggregate industries up to sectors, and present maps at the state, rather than the district-level.

Figure A0: Industrial and Ownership Composition over Time

(a) By Ownership





(b) By Sector

Notes: The figures plot the total number (left panels) and shares (right panels) of projects alive in the data in a given quarter-year by ownership (top panels) or sector (bottom panel) bins. For visualization purposes, we aggregate industries up to sectors. The time dimension extends up to the first quarter of 2020 to exclude the Covid pandemic.

Table A1: Concentration Statistics

	N	Mean	SD	10th	25th	50th	75th	90th
Projects per Company	32456	3.29	18.99	1.00	1.00	1.00	2.00	4.00
Share: Section	16	0.06	0.09	0.01	0.01	0.02	0.05	0.23
HHI: Section	16	0.19						
Share: Industry	134	0.01	0.02	0.00	0.00	0.00	0.01	0.02
HHI: Industry	134	0.04						
Share: State	42	0.02	0.03	0.00	0.00	0.01	0.04	0.05
HHI: State	42	0.06						

Notes: This table reports concentration measures for all projects available in the March 2022 vintage of CapexDx. The number of states includes Union Territories, and exceeds the current number of administrative units due to changes in administrative boundaries over time.

Table A2: Transitions Across Project Stages

	Announced	Completed	No Information	Abandoned	Stalled	Under Imp
Announced	0.00	6.52	20.49	2.47	2.45	68.07
Stalled	10.63	1.31	6.35	22.85	0.00	58.86
Under Imp	0.00	62.15	27.55	3.26	7.04	0.00

Notes: This table constructs a transition matrix across project stages for all projects available in the March 2022 vintage of CapexDx. Rows represent departing states. We only include non-terminal stages, i.e. we exclude completion, abandonment, and loss to follow-up. Columns denote arriving states, which include terminal stages. We only include transitions for which the departing and arriving stage differ. Each entry is the fraction of transitions from the row stage to the column stage (multiplied by 100). For example, 68.07% of all transitions starting from "announced" correspond to transitions into "under implementation".

Table A3: Quarterly Transition Probabilities

	Announced	Completed	No Information	Abandoned	Stalled	Under Imp
Announced	87.92	0.79	2.48	0.30	0.30	8.22
Abandoned	0.66	0.17	0.00	97.98	0.00	1.20
Stalled	0.63	0.08	0.38	1.36	94.05	3.50
Under Imp	0.00	4.02	1.78	0.21	0.46	93.53

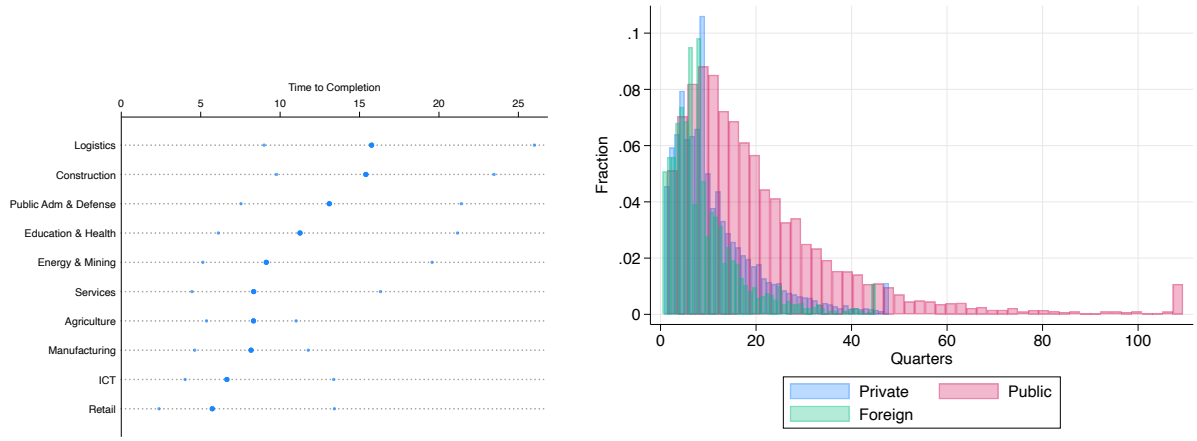
Notes: This table constructs a transition matrix across project stages for all projects available in the March 2022 vintage of CapexDx. Rows represent departing states. We only include non-terminal stages, i.e. we exclude completion, abandonment, and loss to follow-up. In some cases, abandoned projects returns to activity. Since these are exceedingly rare events, we consider abandonment as terminal in all other results in the paper. Columns denote arriving states, which include terminal stages. We include all quarterly transitions. Each entry is the fraction of transitions from the row stage to the column stage (multiplied by 100). For example, 87.92% of all transitions starting from "announced" remain "announced", while 8.22% move into implementation.

Table A4: Cost-Time Schedules

	(1)	(2)	(3)	(4)	(5)
Log Cost	0.178	0.163	0.162	0.152	0.155
	(0.015)	(0.013)	(0.013)	(0.011)	(0.011)
Obs.	29988	29988	29983	29987	29982
Sector		✓	✓		
Industry				✓	✓
Start Year			✓		✓

Notes: This table reports correlations between log time to build and log costs estimated with linear regression from the microdata underlying the binned scatter plots of figure A4. The sample consists of completed projects for which cost data is available. Column (1) reports the bivariate relationship. Column (2) includes sector fixed effects, and column (3) adds year

Figure A3: Disaggregating the Time to Build Distribution

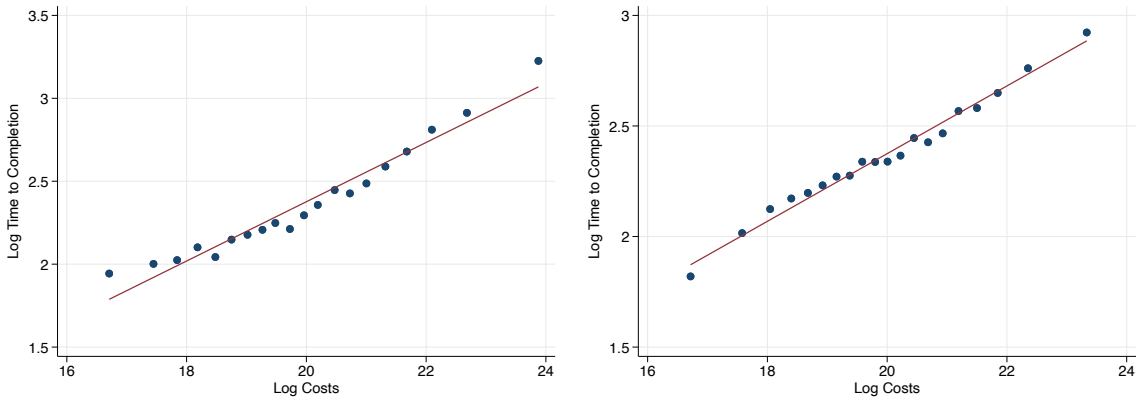


(a) Medians and IQR of Gestation Lags by Sector (b) Distribution of Gestation Lags by Sponsors

Notes: the figures disaggregate the distribution of gestation lags across sectors (panel a) and public vs private ownership (panel b). Panel (a) plots median and interquartile ranges for gestation lags by sector. Sectors are based on a slightly aggregated version of India's NIC-defined sectors, and excludes water, sanitation and sewage (longest median gestation lags) for visualization purposes. Panel (b) plots histograms by private, foreign or public ownership. Distributions are winsorized at the 1st and 99th percentile for visualization purposes. Public ownership includes sponsorship by central, state, or local governments, as well as state-owned enterprises (i.e. public sector is majority shareholder). Private ownership includes any private Indian sponsors.

Figure A4: Cost-Time Schedules

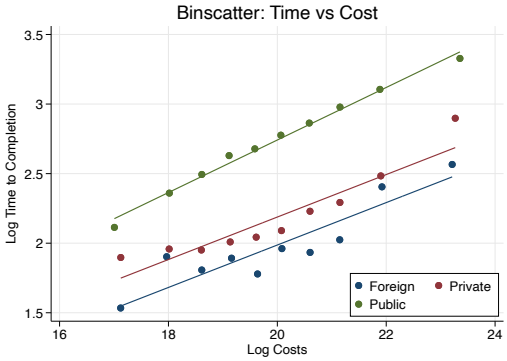
(a) Bivariate Correlation (b) Within-Industry Correlation

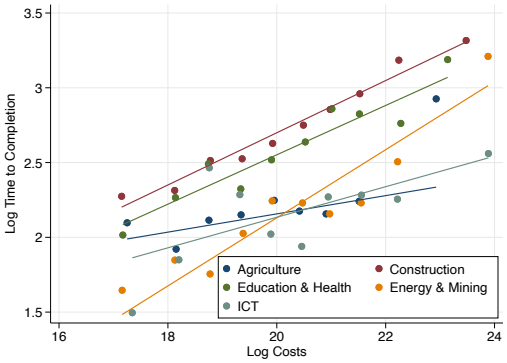


Notes: the figures plot binned scatterplots of (log) time to completion on (log) costs. The sample is restricted to all completed projects in the CapexDx data with non-missing cost data. Panel (a) plots the bivariate non-parametric relationship. Panel (b) first residualizes by industry dummies.

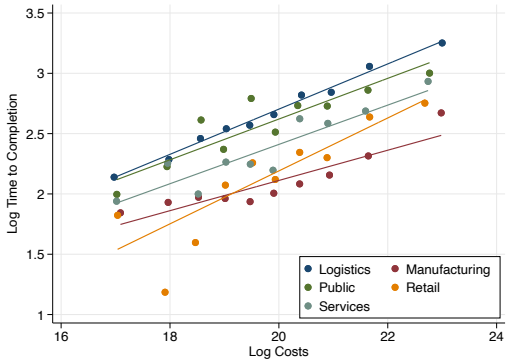
Figure A4: Cost-Time Schedule by Subgroups

(a) By Ownership





(b) By Sector



(c) By Sector

Notes: The figure disaggregates the binned scatter plots of log time to build on log costs (see panel a of figure A4) by sponsorship (panel a) and sectors (panels b and c, split for the sake of visualization).

Table A5: Cross-Sectional Variance Decompositions: Time to Completion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R^2	0.239	0.302	0.285	0.395	0.409	0.410	0.396	0.441	0.579
Unc. Var					0.014	0.015	0.001	0.046	
Partial R^2					0.023	0.024	0.002	0.077	
Ownership FE						✓		✓	
State FE					✓			✓	
Sector FE	✓			✓	☒	☒	☒	☒	
Industry FE		✓							
Year Started FE			✓	✓	☒	☒	☒	☒	✓
Type of unit FE							✓	✓	
Firm FE									✓

Notes: the table provides a variance accounting for completed projects. The first row reports the R^2 of a linear regression of gestation lags on the fixed effects indicated by ✓ in the bottom part of the table. In columns (5)-(8), all regressions include sector and year started fixed effects (marked by ☒); and the additional explanatory power of the added fixed effects (marked by ✓) is presented with uncorrelated variance shares (the difference between the R^2 to the R^2 in column 4) and the partial R^2 (the uncorrelated variance share divided by the unexplained variance share in column 4). Lower values of the uncorrelated variance share indicate that the additional predictors have low additional explanatory powers relative to the predictors included in the baseline model (column 4). Lower values of the partial R^2 indicate that the additional predictors have low explanatory power for the residual variation left from the baseline model (column 4). Type of Unit captures whether the project is a new structure, a substantial renovation, or a modernization of an existing structure; and type of ownership captures private (Indian), foreign or public sponsorship.

C Additional Empirical Results

Table A7: Effects of Asset Quality Review on Credit Supply

	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.0021	-0.0069***	-0.0027*	-0.0046*	-0.0085***	-0.0051**
	(0.0015)	(0.0018)	(0.0015)	(0.0024)	(0.0028)	(0.0024)
Outc Mean	-0.08	-0.08	-0.08	-0.10	-0.10	-0.10
Obs	194072	194072	194072	78827	78827	78827
Full Sample	✓	✓	✓			
Hazard Sample				✓	✓	✓
Borrower + Year FE	✓		✓	✓		✓
Borrower x Year FE		✓			✓	
Firm Controls			✓			✓

Notes: the table reports estimates of β from the following model:

$$\Delta\text{Loans}_{bft} = \text{Firm-Year}_{ft} + \beta \times \text{Bank Shock}_{bt} + \varepsilon_{bft}$$

where ΔLoans_{bft} is the growth rate of loans between $t-1$ and t, constructed as in Davis and Haltiwanger (1992). The sample consists of firm-bank relationships for 2013-2019, conditional on an existing relationship (positive outstanding loans) in the 2013-2015 period. Exposure is defined as the difference between required provision after the audit and the original provisions, scaled by total bank assets. Coefficient estimates are read as the effect on the outcome for a one standard-deviation increase in lender exposure. For example, column (1) reports that moving from the lender with average exposure to a lender with one-standard deviation higher exposure decreases outstanding loans by -0.21 percentage points, relative to a mean growth rate of 8 percentage points. In columns (1)-(3), the sample comprises all borrower-lender pairs in our MCA-Prowess merged sample. In columns (4)-(6), the sample is restricted to firms for which we eventually observe projects in our hazard regressions (see model (1) and table 2). Columns (2) and (5) include borrower-by-year fixed effects. Columns (1) and (3) include borrower, and year fixed effects. Columns (3) and (6) add firm controls. Firm controls include sales, sales growth, profitability, debt over equity, book leverage, equity issuances, cash over liquid assets, and debt over EBITDA. All firm controls are winsorized at the 1st and 99th percentile, and then standardized. All firm controls are lagged by one-period. Standard errors are clustered at the lender level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table A6: Effects of Asset Quality Review on Credit Supply

	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.0517***	-0.0508***	-0.0513***	-0.0497***	-0.0485***	-0.0491***
	(0.0106)	(0.0119)	(0.0120)	(0.0122)	(0.0130)	(0.0131)
Outc Mean	2497.20	2497.47	2497.47	4450.34	4450.34	4450.34
Obs	268858	268827	268827	109929	109929	109929
Full Sample	✓	✓	✓			
Hazard Sample				✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓
Borrower by Year FE	✓			✓		
Borrower and Year FE		✓	✓		✓	✓
Firm Controls			✓			✓

Notes: the table reports PPML estimates of the semi-elasticity of outstanding loans within a borrower-lender pair in a given year to lender exposure to the Asset Quality Review. The sample consists of a balanced panel of firm-bank relationships for 2013-2019, conditional on an existing relationship (positive outstanding loans) in the 2013-2015 period. Exposure is defined as the difference between required provision after the audit and the original provisions, scaled by total bank assets. Coefficient estimates are read as the percent effect on the outcome for a one standard-deviation increase in lender exposure. For example, column (1) reports that moving from the lender with average exposure to a lender with one-standard deviation higher exposure decreases outstanding loans by 5.08%. In columns (1)-(3), the sample comprises all borrower-lender pairs in our MCA-Prowess merged sample. In columns (4)-(6), the sample is restricted to firms for which we eventually observe projects in our hazard regressions (see model (1) and table 2). Columns (1) and (4) include lender and borrower-by-year fixed effects. Columns (2) and (5) include lender, borrower, and year fixed effects. Columns (3) and (6) add firm controls. Firm controls include sales, sales growth, profitability, debt over equity, book leverage, equity issuances, cash over liquid assets, and debt over EBITDA. All firm controls are winsorized at the 1st and 99th percentile, and then standardized. All firm controls are lagged by one-period. Standard errors are clustered at the lender level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table A8: Effects of Firm-Level Credit Supply Shocks on Project Completion Hazards

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure (Pre)	0.1057***	0.0772***	0.0766***	0.0754***	0.0749***	0.0844***	0.0845***
	(0.0277)	(0.0273)	(0.0273)	(0.0267)	(0.0267)	(0.0265)	(0.0266)
Exposure (2015)	0.1067***	0.0701***	0.0698***	0.0691***	0.0690***	0.0823***	0.0830***
	(0.0275)	(0.0270)	(0.0269)	(0.0261)	(0.0261)	(0.0265)	(0.0266)
DepVar Mean	0.0397	0.0397	0.0397	0.0397	0.0397	0.0414	0.0414
Observation	122123	122123	122123	122123	122123	116788	116788
Age Splines	✓	✓	✓	✓	✓	✓	✓
Firm FE		✓	✓	✓	✓	✓	✓
State x Year FE		✓	✓	✓	✓	✓	✓
Sector x Year FE				✓	✓		
Industry x Year FE						✓	✓
Firm Controls			✓		✓		✓

Notes: the table reports PPML estimates of the semi-elasticity of project-level hazards to firm exposure to the Asset Quality Review (see model (1)). The sample consists of projects observed quarterly between 2013-2019. Each row corresponds to a measure of firm exposure. Firm exposure is defined as the weighted-average of lender exposure, where weights vary by row. "(Pre)" indicates weights are constructed as average outstanding loans between 2013-2015 for a borrower-lender pair relative to average outstanding loans between 2013-2015 for a given borrower. "(2015)" indicates weights are constructed as outstanding loans in 2015 between a borrower-lender pair relative to outstanding loans in 2015 for a given borrower. Coefficient estimates are interpreted as the percent effect on the outcome for a one standard-deviation increase in firm exposure. For example, column (1) reports that moving from a firm with average exposure to a firm with one-standard deviation higher exposure increases the hazard by 10.57%. Age splines refer to cubic splines on a project's age (measured in quarters). Firm controls include sales, sales growth, profitability, debt over equity, book leverage, equity issuances, cash over liquid assets, and debt over EBITDA. All firm controls are winsorized at the 1st and 99th percentile, and then standardized. All firm controls are lagged by one-period. The reduction in sample size from columns (5) to columns (6) and (7) results from separation of additional observations by the more granular industry-by-year fixed effects relative to the sector-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table A9: Effects of Firm-Level Credit Supply Shocks on Project Completion Hazards

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure	0.0057***	0.0030**	0.0029**	0.0028**	0.0027**	0.0029***	0.0028**
	(0.0017)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0011)	(0.0011)
DepVar Mean	0.0397	0.0397	0.0397	0.0397	0.0397	0.0397	0.0397
Observation	122123	122123	122123	122123	122123	122100	122100
Age Splines	✓	✓	✓	✓	✓	✓	✓
Firm FE		✓	✓	✓	✓	✓	✓
State x Year FE		✓	✓	✓	✓	✓	✓
Sector x Year FE				✓	✓		
Industry x Year FE						✓	✓
Firm Controls			✓		✓		✓

Notes: the table reports linear regression estimates of the effect of firm exposure to the Asset Quality Review on project hazards (see model (1)). The sample consists of projects observed quarterly between 2013-2019. Firm exposure is defined as the weighted-average of lender exposure, where weights correspond to outstanding loans in the previous year. Coefficient estimates are interpreted as the level effect on the outcome for a one standard-deviation increase in firm exposure. For example, column (1) reports that moving from a firm with average exposure to a firm with one-standard deviation higher exposure increases the hazard by 0.57 percentage points, relative to an unconditional completion probability of 3.97 percentage points. Age splines refer to cubic splines on a project's age (measured in quarters). Firm controls include sales, sales growth, profitability, debt over equity, book leverage, equity issuances, cash over liquid assets, and debt over EBITDA. All firm controls are winsorized at the 1st and 99th percentile, and then standardized. All firm controls are lagged by one-period. The reduction in sample size from columns (5) to columns (6) and (7) results from separation of additional observations by the more granular industry-by-year fixed effects relative to the sector-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table A10: Effects of Firm-Level Credit Supply Shocks on Project Starts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure (Pre)	-0.0740***	-0.0708**	-0.0673**	-0.0808**	-0.0753**	-0.0562*	-0.0556*
	(0.0278)	(0.0324)	(0.0321)	(0.0321)	(0.0319)	(0.0305)	(0.0303)
Exposure (2015)	-0.0755***	-0.0711**	-0.0676**	-0.0818***	-0.0765**	-0.0577*	-0.0572*
	(0.0280)	(0.0321)	(0.0319)	(0.0317)	(0.0315)	(0.0298)	(0.0296)
DepVar Mean	0.8362	0.8362	0.8362	0.8362	0.8362	0.8326	0.8326
Observation	8994	8994	8994	8994	8994	8869	8869
Firm FE		✓	✓	✓	✓	✓	✓
Year FE		✓	✓				
NIC Section x Year FE				✓	✓		
NIC Division x Year FE						✓	✓
Firm Controls			✓		✓		✓

Notes: the table reports PPML estimates of the semi-elasticity of firm-level project starts to firm exposure to the Asset Quality Review (see model (2)). The sample consists of the Capex-Prowess matched sample of firms observed yearly between 2013-2019. Each row corresponds to a measure of firm exposure. Firm exposure is defined as the weighted-average of lender exposure, where weights vary by row. "(Pre)" indicates weights are constructed as average outstanding loans between 2013-2015 for a borrower-lender pair relative to average outstanding loans between 2013-2015 for a given borrower. "(2015)" indicates weights are constructed as outstanding loans in 2015 between a borrower-lender pair relative to outstanding loans in 2015 for a given borrower. Coefficient estimates are interpreted as the percent effect on the outcome for a one standard-deviation increase in firm exposure. For example, column (1) reports that moving from a firm with average exposure to a firm with one-standard deviation higher exposure reduces project starts by 7.4%. NIC Section and Division classifications are constructed from NIC codes and categorizations. Firm controls include sales, sales growth, profitability, debt over equity, book leverage, equity issuances, cash over liquid assets, and debt over EBITDA. All firm controls are winsorized at the 1st and 99th percentile, and then standardized. All firm controls are lagged by one-period. The reduction in sample size from columns (5) to columns (6) and (7) results from separation of additional observations by the more granular division-by-year fixed effects relative to the section-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table A11: Effects of Firm-Level Credit Supply Shocks on Project Starts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure	-0.0560***	-0.0534**	-0.0520**	-0.0574**	-0.0562**	-0.0471**	-0.0462**
	(0.0195)	(0.0226)	(0.0223)	(0.0226)	(0.0223)	(0.0218)	(0.0215)
DepVar Mean	0.8362	0.8362	0.8362	0.8362	0.8362	0.8281	0.8281
Observation	8994	8994	8994	8994	8994	8941	8941
Firm FE		✓	✓	✓	✓	✓	✓
Year FE		✓	✓				
NIC Section x Year FE				✓	✓		
NIC Division x Year FE						✓	✓
Firm Controls			✓		✓		✓

Notes: the table reports linear regression estimates of the effect of firm exposure to the Asset Quality Review on firm-level project starts (see model (2)). The sample consists of the Capex-Prowess matched sample of firms observed yearly between 2013-2019. Each row corresponds to a measure of firm exposure. Firm exposure is defined as the weighted-average of lender exposure, where weights correspond to outstanding loans in the previous year. Coefficient estimates are interpreted as the level effect on the outcome for a one standard-deviation increase in firm exposure. For example, column (1) reports that moving from a firm with average exposure to a firm with one-standard deviation higher exposure reduces project starts by 0.056 projects relative to an unconditional mean of 0.8362 projects. NIC Section and Division classifications are constructed from NIC codes and categorizations. Firm controls include sales, sales growth, profitability, debt over equity, book leverage, equity issuances, cash over liquid assets, and debt over EBITDA. All firm controls are winsorized at the 1st and 99th percentile, and then standardized. All firm controls are lagged by one-period. The reduction in sample size from columns (5) to columns (6) and (7) results from separation of additional observations by the more granular division-by-year fixed effects relative to the section-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table A12: Balance Tests: Cross-Section

	(1)	(2)	(3)
Log Sales	3.644	3.967	-0.1998**
			(0.0826)
Sales Growth	0.040	0.043	-0.0002
			(0.0525)
Profitability (EBIT)	0.052	0.062	-0.0149
			(0.0325)
EBIT < 0	0.157	0.117	0.0419
			(0.0402)
Debt/Equity	57.100	42.253	-1.9474
			(4.5947)
Book Leverage	35.800	28.777	1.6844
			(3.1223)
Equity Issuance	-0.020	0.134	-0.2403**
			(0.1041)
Cash/Liquid Assets	0.156	0.111	0.0150
			(0.0116)
Debt/EBIT	0.103	2.566	-3.6173
			(2.8500)

Notes: the table reports linear regression estimates of covariate balance across sponsor exposure to the Asset Quality Review. In particular, we regress firm-level characteristics averaged over 2013-2015 X_f on average firm exposure over the 2016-2019 period $Expo_f$, where firm exposure is defined as the weighted-average of lender exposure and weights correspond to outstanding loans in the previous year. Each row corresponds to one of our firm controls. Columns (1) and (2) report raw means conditional on a binary exposure indicator. Column (3) reports the coefficient on the exposure variable in the cross-sectional linear regression model. All outcomes are winsorized at the 2.5th and 97.5th percentile, and then standardized. Standard errors are heteroscedasticity-robust and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table A13: Balance Tests: Panel

	(1)	(2)	(3)
Log Sales	2.849	3.838	-0.3798
			(0.4663)
Sales Growth	0.085	0.045	-0.1046
			(0.0782)
Profitability (EBIT)	0.016	0.074	-0.2861**
			(0.1177)
EBIT < 0	0.179	0.119	0.0906
			(0.0644)
Debt/Equity	85.557	46.410	-23.0500
			(46.1865)
Book Leverage	51.422	30.764	-17.9970
			(24.3064)
Equity Issuance	0.108	-0.104	-0.1340
			(0.1350)
Cash/Liquid Assets	0.225	0.140	-0.0710*
			(0.0377)
Debt/EBIT	-6.070	2.478	0.2829
			(5.7189)

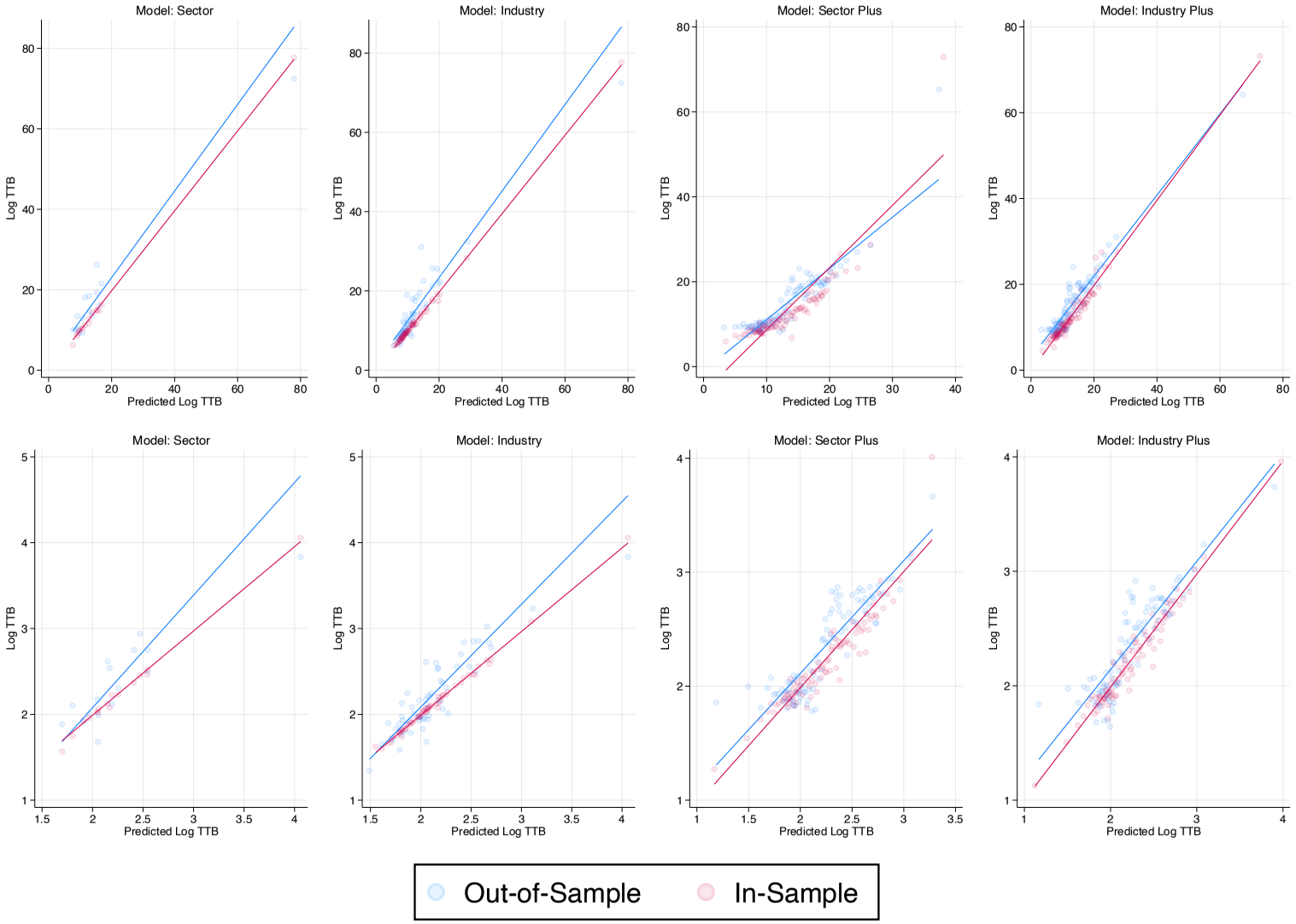
Notes: the table reports linear regression estimates of covariate balance across sponsor exposure to the Asset Quality Review. The sample consists of the Capex-Prowess matched sample of firms observed yearly between 2013-2019. In particular, we regress lagged firm-level characteristics $X_{f,t-1}$ on contemporaneous firm exposure $Expo_{f,t}$. Each row corresponds to one of our firm controls. Firm exposure is defined as the weighted-average of lender exposure, where weights correspond to outstanding loans in the previous year. Columns (1) and (2) report raw means conditional on a binary exposure indicator. Column (3) reports the coefficient on the exposure variable in the panel linear regression model, including firm and year fixed effects. All outcomes are winsorized at the 2.5th and 97.5th percentile, and then standardized. Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table A14: Predicting TTB: Model Comparison

	Time to Build				Log Time to Build			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: RMSE				
Out-of-Sample	13.718	13.382	13.552	13.525	0.860	0.822	0.848	0.854
In-Sample	11.011	10.562	11.639	10.436	0.819	0.786	0.791	0.778
				Panel B: R-Squared				
Out-of-Sample	0.123	0.166	0.144	0.148	0.110	0.187	0.134	0.122
In-Sample	0.386	0.435	0.314	0.448	0.138	0.206	0.196	0.223
				Panel C: OLS				
Slope	1.076	1.093**	1.208***	0.945	1.312***	1.196***	0.989	0.945***
	(0.057)	(0.046)	(0.033)	(0.040)	(0.023)	(0.017)	(0.015)	(0.015)
Constant	1.492**	1.471***	-1.052**	2.983***	-0.549***	-0.306***	0.135***	0.252***
	(0.710)	(0.561)	(0.417)	(0.497)	(0.051)	(0.038)	(0.033)	(0.034)
Sector FE	✓		✓		✓		✓	
Industry FE		✓		✓		✓		✓
State FE			✓	✓			✓	✓
Ownership FE			✓	✓			✓	✓
Type of Unit FE			✓	✓			✓	✓

Notes: the table compares the predictive ability of different models for time to build. Each column correspond to a different (linear) predictive model including (non-parametrically) the covariates marked by ✓ in the bottom panel of the table. Panel A reports root-mean squared errors and Panel B reports R^2 of each model for both the estimating sample ("In-sample") and for the hazard regression sample ("Out-of-Sample"). Panel C reports OLS estimates a linear regression of observed gestation lags on predicted gestation lags for the hazard regression sample (i.e. the target sample of interest). Slope values closer to one and constant values closer to zero indicate more proximity to the 45 degree line. Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively. In Panel C, the null hypothesis is that the slope is equal to 1, and that the constant is equal to zero. Tests for slope and constant are conducted separately rather than jointly. We use the model of column (2) for predicting project stages.

Figure A14: Predictive Models of Time to Build



Notes: The figure plots binned scatter plots and lines of best fit for different predictive models of time to build. The y-axis plots either (quarterly) time to build in levels or in logs. The x-axis plots the predictions obtained from each model. If the model perfectly predicted the data, "in sample" dots would line up perfectly with the red line. The "in-sample" sample is all projects completed prior to 2015 that are not included in the hazard regression sample. The "out-of-sample" sample in blue is the hazard regression sample. The first row predicts gestation lags in levels. The second row predicts gestation lags in logs. Columns correspond to different models. "Sector" includes only sector dummies. "Industry" moves to industry dummies. "Plus" indicates that we add all other predictors in column 8 of Table A5 excluding year started.

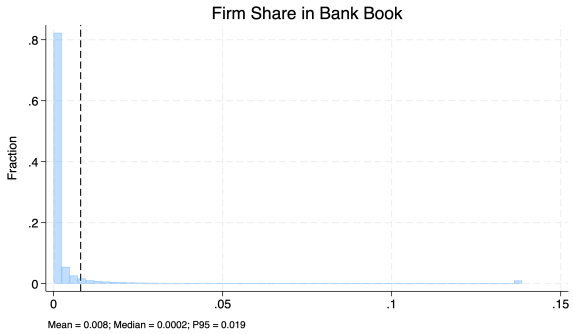
Table A15: Heterogeneous Effects by Initial Age

	(1)	(2)	(3)	(4)
Exposure	0.094***	0.090***	0.099***	0.096***
	(0.025)	(0.026)	(0.026)	(0.026)
Age x Exposure	0.060***	0.062***	0.066***	0.068***
	(0.023)	(0.023)	(0.025)	(0.025)
Initial Age FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
State x Year FE	✓	✓	✓	✓
Sector x Year FE	✓	✓		
Industry x Year FE			✓	✓
Firm Controls		✓		✓

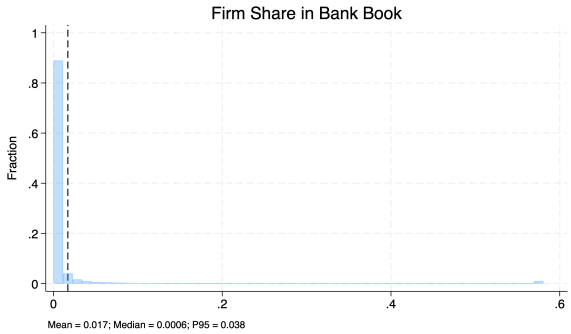
Notes: the table reports PPML estimates of the semi-elasticity of project-level hazards to sponsor exposure to the Asset Quality Review. The sample consists of projects observed quarterly between 2013-2019. Firm exposure is defined as the weighted-average of lender exposure, where weights correspond to outstanding loans in the previous year. The proxy for stage is Initial Age, constructed as age of the project when first observed in the sample. This measure is winsorized at the 1st and 99th percentile, and then standardized before being included in the regression model. The coefficient on exposure is interpreted as the percent effect on the outcome for a one standard-deviation increase in firm exposure for the project with mean proxy stage. The coefficient on the interaction is interpreted as the change in the main effect resulting from a one-standard deviation level change in proxy stage. For example, the first row in column (1) reports that moving from a sponsor with average exposure to a sponsor with one-standard deviation higher exposure increases the hazard by 9.4% for the project at the mean proxy stage. The second row in column (1) reports that if the project had been one standard deviation above (below) the mean stage at the time of the shock, the effect would have incresed (declined) by 6%, for a total effect of 15.4% (3.4%). In order to avoid strong collinearity concerns between the age spline, initial age, and the time fixed effects, we omit the age spline, and control non-parameterically for the initial age. Firm controls include sales, sales growth, profitability, debt over equity, book leverage, equity issuances, cash over liquid assets, and debt over EBITDA. All firm controls are winsorized at the 1st and 99th percentile, and then standardized. All firm controls are lagged by one-period. The reduction in sample size from columns (1) and (2) to columns (3) and (4) results from separation of additional observations by the more granular industry-by-year fixed effects relative to the sector-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Figure A15: Distribution of Firm Shares of Bank Charges

(a) Universe of Charges



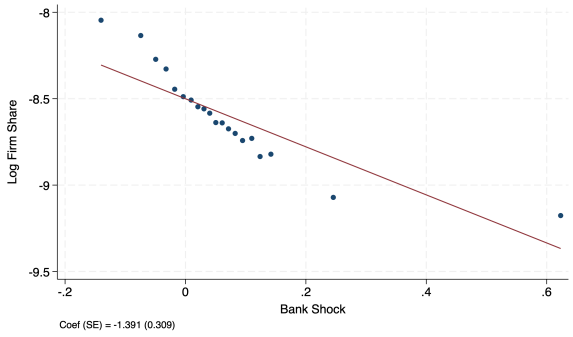
(b) Firms in Hazard Regression



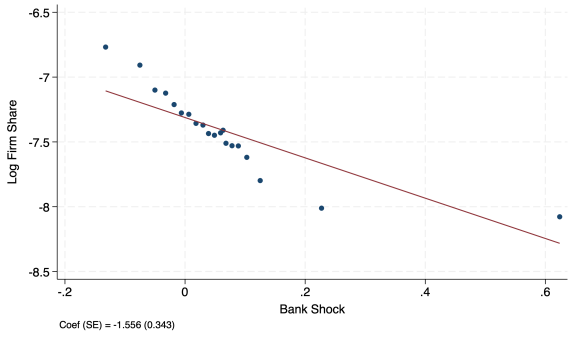
Notes: the figures plot the distribution of firm shares in bank charges in the MCA registry. We compute $s_{bft} = {}^{Loans_{bft}}/_{\sum_{f'} Loans_{bf't}}$ for both the universe of charges (left panel) and for firms that eventually make to our regression sample (right panel). The statistics at the bottom represent the mean, median and 95th percentile of the distribution. Histograms are winsorized at the 99th percentile for visibility.

Figure A15: Correlations of Firm Shares and Future Bank Exposure

(a) Universe of Charges



(b) Firms in Hazard Regression



Notes: the figures plot binscatters of (log) firm shares $s_{bft} = {}^{Loans_{bft}}/_{\sum_{f'} Loans_{bf't}}$ on one-period ahead bank exposure Bank Shock$_{b,t+1}$ for both the universe of charges (left panel) and for firms that eventually make to our regression sample (right panel). Consistent with the timing of our regressions, we restrict to FY 2013-2019 and control for firm and time fixed effects. The notes on the bottom of the charts reproduce the coefficient on the forward bank shocks obtained by regressing the log share log s_{bft} on future exposure Bank Shock$_{b,t+1}$, controlling for time and firm fixed effects and clustering standard errors at the lender level.

D Backfilling, Censoring, and Selection

CapexDx strives to provide maximal coverage, despite the non-administrative nature of the data collection process. As a result, some project histories are backfilled. Once CapexDx obtains information on an already ongoing project, it reconstructs the project history by active research on the public domain and contact with project sponsors.

On the one hand, such retroactive filling improves coverage. On the other hand, it introduces a potential threat to our empirical strategy. The concern is that the RBI audits – and their resulting firm-level disruptions – alter the data collection process. For example, CapexDx could become less likely to find data on projects. This opens up space for a delicate form of selection bias: the sample of projects collected after the shock may differ from the sample of projects before the shock.[56]

If the resulting selection into sample is balanced across the treated and untreated group, it is *independent* of treatment. Our estimates will have a causal interpretation *within the selected sample* (Hernan and Robins, 2023). That is, we can still identify the effect of exposing units to the shock relative to a counterfactual of no exposure; but we can only speak to the effect on the units that eventually make it into our dataset. The causal effect on censored units is not identified from observational data. This concern is present in *any* study for which data collection might be affected by the treatment of interest (e.g. studies leveraging survey data).

We would not be able to make causal statements, even within the noncensored sample, if the treatment induced differential censoring. To be concrete, let's suppose then that CapexDx becomes less able to obtain data on treated relative to untreated projects. Perhaps, firms more exposed to the banking shock stop sharing information about their projects on the public domain or taking the time to respond to CapexDx inquiries. Let's further suppose there is no backfilling, so any new projects for which CapexDx obtains data are always recent starts.

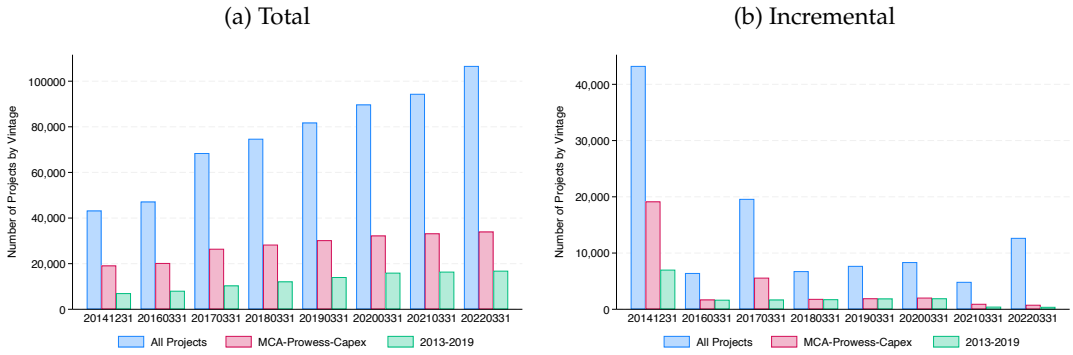
The concern then is that the observed sample would be skewed towards ***fewer*** early projects among the treated group. Moreover, since older projects are more likely to be completed, comparing treated and untreated projects within the uncensored sample incurs a sample selection bias. That is, we may observe an association between completion and treatment, even if treatment does not influence completion. The observed association results simply from the missing early projects among the treated. If such projects had been included in the data, we might have been able to recover the true null causal effect of treatment on project completions. In a nutshell, there is no causal effect of treatment on completion, but only a causal effect of treatment on selection into the data. Matters are further complicated by the presence of backfilling. Projects entering in any given vintage of the data may have

[56]Such form of censoring can be pervasive in retrospective studies. Duration models allow us to learn from *right-censored* observations under the assumption of noninformative censoring (conditional on the model's covariates), but are not immune to the selective censoring concerns we highlight here.

been started in the more distant past. But the general concern remains: we worry that fewer young projects enter the sample for the treated group after the shock.

We provide two analyses to soothe concerns that our results are driven by sample selection bias due to differential changes in the data collection process for treated versus untreated projects. First, we restrict our completion analyses to projects that were in data vintages *prior* to the first audits. Even if the data collection process differentially changed following the shocks, projects in vintages prior to the shock would not have been affected by such changes. This sample is thus immune to the selection concerns. Second, we test a direct implication of differential censoring due to differential backfilling. If CapexDx had become less able to backfill data on treated relative to untreated projects, we should observe a downward trend in the number of treated projects relative to untreated projects before the shock. We thus test whether exposure predicts differential pre-trends in firm-level project stocks.

Figure A15: Total and incremental counts of projects by vintage



Notes: The figure plots the total (panel a) or incremental (panel b) number of projects for each available vintage of the CapexDx dataset. The x-axis indicates the vintage by its release date. Within a given vintage, we plot counts for three samples. The blue (left-most) bar corresponds to all projects. The red (middle) bar corresponds to projects in the MCA-Prowess-Capex matched dataset. The green (left-most) bar corresponds to projects in the 2013-2019 window around adoption of the Asset Quality Review.

For our first analysis, we collect previous vintages of CapexDx. The first vintage was released on December 31st, 2014. It thus predates the first Asset Quality Review audit. Further vintages were released yearly on March 31st starting in 2016, hence after the first audits had been carried out. Figure A15 plots the total number of projects in each vintage, as well as the number of projects added in each vintage. We split projects in three groups: all projects in the CapexDx data, projects with sponsors in the MCA-Prowess-Capex matched sample, and projects in the estimating sample for the completion regressions.

We reestimate the completion regressions in the first vintage subsample. Table A16 reports results. In the first row, the firm-level exposure variable aggregates bank-level shocks using lagged, time-varying weights (LTV). The point estimates are quantitatively similar to those obtained without restricting the sample. The standard errors are larger, but this is un-

Table A16: Effect on Completion Hazards: Subset of First Vintage Projects: Panel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure (LTV)	0.0213	0.0637	0.0627	0.0580	0.0578	0.0469	0.0449
	(0.0302)	(0.0422)	(0.0422)	(0.0425)	(0.0425)	(0.0453)	(0.0457)
Exposure (PreW)	0.0260	0.0802**	0.0817**	0.0782*	0.0804*	0.0717*	0.0743*
	(0.0306)	(0.0409)	(0.0410)	(0.0418)	(0.0420)	(0.0434)	(0.0437)
Exposure (2015W)	0.0241	0.0769*	0.0789**	0.0756*	0.0783*	0.0697*	0.0726*
	(0.0299)	(0.0397)	(0.0397)	(0.0405)	(0.0405)	(0.0417)	(0.0419)
DepVar Mean	0.0385	0.0385	0.0385	0.0385	0.0385	0.0408	0.0408
Observation	53750	53741	53741	53741	53741	50277	50277
Age Splines	✓	✓	✓	✓	✓	✓	✓
Firm FE		✓	✓	✓	✓	✓	✓
State x Year FE		✓	✓	✓	✓	✓	✓
Sector x Year FE				✓	✓		
Industry x Year FE						✓	✓
Firm Controls			✓		✓		✓

Notes: the table reports PPML estimates of the semi-elasticity of project-level hazards to firm exposure to the Asset Quality Review (see model (1)). The sample consists of projects observed quarterly between 2013-2019; and is further ***restricted to projects that were present in the data as of the first vintage (Dec 31, 2014)***, thereby preceding the first Asset Quality Review. Firm exposure is defined as the weighted-average of lender exposure and weights vary by row. "(LTV)" indicates lagged, time-varying weights, as in our baseline results. "(Pre)" indicates weights are constructed as average outstanding loans between 2013-2015 for a borrower-lender pair relative to average outstanding loans between 2013-2015 for a given borrower. "(2015)" indicates weights are constructed as outstanding loans in 2015 between a borrower-lender pair relative to outstanding loans in 2015 for a given borrower. Coefficient estimates are interpreted as the percent effect on the outcome for a one standard-deviation increase in firm exposure. For example, row 1 of column (1) reports that moving from a firm with average exposure to a firm with one-standard deviation higher exposure increases the hazard by 2.13%. Age splines refer to cubic splines on a project's age (measured in quarters). Firm controls include sales, sales growth, profitability, debt over equity, book leverage, equity issuances, cash over liquid assets, and debt over EBITDA. All firm controls are winsorized at the 1st and 99th percentile, and then standardized. All firm controls are lagged by one-period. The reduction in sample size from columns (5) to columns (6) and (7) results from separation of additional observations by the more granular industry-by-year fixed effects relative to the sector-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table A17: Cross-Sectional Balance Tests: Project Stocks

	Mean | Exp = 0 (1)	Mean | Exp > 0 (2)	Mean | Exp (3)
Active Projects	2.441	4.185	-3.3262***
			(1.1054)
Projects Started	0.504	0.683	-0.5060**
			(0.2276)
Projects Completed	0.233	0.342	-0.4336***
			(0.0998)
Projects Abandoned	0.043	0.075	-0.0377
			(0.0415)
Projects Censored	0.100	0.192	-0.0240
			(0.0779)
Projects Under Implementation	1.428	2.415	-1.9943***
			(0.6739)
Projects Announced	0.976	1.599	-1.3409***
			(0.4452)
Projects Stalled	0.176	0.355	0.0812
			(0.1501)
Exposure			✓

Notes: the table reports linear regression estimates of covariate balance across firm exposure to the Asset Quality Review. In particular, we regress firm-level outcomes averaged over 2013-2015 Y_f on average firm exposure over the 2016-2019 period $Expo_f$, where firm exposure is defined as the weighted-average of lender exposure, where weights correspond to outstanding loans in the previous year. Each row corresponds to either a stock (active, announced, under implementation, or stalled) or flow (completed, censored, abandoned, started) of projects. Columns (1) and (2) report raw means conditional on a binary exposure indicator. Column (3) reports the coefficient on the exposure variable in the cross-sectional linear regression model. Standard errors are heteroscedasticity-robust and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

surprising given the sample size is effectively halved. Despite the reduced power, the similar point estimates between the two specifications is highly encouraging: if bias was a concern, point estimates would have changed considerably between the two exercises.

In the second and third rows, the firm-level exposure variables weigh bank shocks by pre-audit exposures. The second row averages outstanding loans between 2013 and 2015 (PreW), whereas the third row simply takes the 2015 outstanding loan amounts (2015W). The standard errors are indistinguishable from those in the first row, but the point estimates are larger and statistically significant. This increase in point estimates might appear puzzling at first, but would be consistent with later-year weights becoming smaller if firms slowly substitute away from more exposed banks.

The results in Table A16 corroborate that our main results are not driven by treatment inducing differential sample selection into later vintages. It does not, however, speak to the possibility of such differential censoring being present in the data. An implication of such selection would be differential pre-trends in the number of projects among treated and

Table A18: Panel Balance Tests: Project Stocks

	Mean | Exp = 0	Mean | Exp > 0	Mean | Exp	Mean | Exp
	(1)	(2)	(3)	(4)
L1 Active Projects	2.987	3.408	-2.0376***	-0.1223
			(0.5203)	(0.2349)
L1 Projects Started	0.473	0.649	0.0162	-0.1163
			(0.1167)	(0.1217)
L1 Projects Completed	0.255	0.332	-0.0630	0.0410
			(0.0730)	(0.0749)
L1 Projects Abandoned	0.042	0.032	-0.0510***	0.0292
			(0.0174)	(0.0242)
L1 Projects Censored	0.124	0.174	-0.0013	-0.0368
			(0.0414)	(0.0583)
L1 Projects Under Implementation	1.768	2.038	-1.3085***	-0.1103
			(0.3334)	(0.1944)
L1 Projects Announced	1.104	1.241	-0.6835***	-0.0655
			(0.2054)	(0.1568)
L1 Projects Stalled	0.228	0.259	-0.1360**	-0.0042
			(0.0572)	(0.0481)
Exposure			✓	✓
Firm + Year FE				✓

Notes: the table reports linear regression estimates of covariate balance across firm exposure to the Asset Quality Review. The sample consists of the Capex-Prowess matched sample of firms observed yearly between 2013-2019. In particular, we regress lagged firm outcomes $Y_{f,t-1}$ on contemporaneous firm exposure $Expo_{f,t}$. Each row corresponds to either a stock (active, announced, under implementation, or stalled) or flow (completed, censored, abandoned, started) of projects. Firm exposure is defined as the weighted-average of lender exposure, where weights correspond to outstanding loans in the previous year. Columns (1) and (2) report raw means conditional on a binary exposure indicator. Column (3) reports the coefficient on the exposure variable in the panel linear regression model (balance in levels). Column (4) adds firm and time fixed effects (balance in within-unit trends). Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

untreated firms. We test for this possibility as follows. First, we ask whether firms on average more exposed to the shock exhibit fewer projects or fewer starts before the audits ever began. The last column in table A17 shows that higher average exposure ex post predicts ex ante differences in firms' project stocks (each row corresponds to a different dependent variable). Prior to the shock, more exposed firms have on average fewer projects, start fewer projects, and complete fewer projects.

Table A17 performs a cross-sectional balance test. Such balance in levels would be reassuring, but is far more stringent than what's implied by the differential selection story (and than what's required by our identifying assumption). Level differences could be driven, for instance, by permanent differences in the set of firms that are eventually exposed or not. Our panel regressions control non-parametrically for such possibility with firm fixed effects; but firm-level regressions – as in table A17 cannot. We thus move to a panel regression, and test whether contemporaneous exposure predicts a decline in lagged number of projects.

Table A18 collects the results. The last two columns both regress lagged variables on contemporaneous treatments. The third column does not include any fixed effects. Consistent with table A17 , we cannot rule out differences in levels. But we can rule out differential pre-trends. Including firm and time effects in the last column, the predictability vanishes; point estimates become small in magnitude and economically insignificant. The results for number of projects is at odds with the predictions of differential selection.

Admittedly, our evidence directly ruling out differential backfilling by treatment status is suggestive. It reflects a fundamental data limitation. Nonetheless, we are reassured by the two robustness checks we started with. First, restricting the sample to projects already present in the 2014 vintage does not substantially alters the results from our completion regressions. Such robustness makes it unlikely that our main results are driven by sample selection concerns arising from differential changes in data collection after the shock for treated relative to untreated firms. Second, we fail to reject equal pre-trends on the number of started projects for treated versus untreated projects. Such evidence weighs against a direct implication of the differential censoring concern.

E Changes in Scope

In the main text, we argued that our results were not driven by firms simply changing the scope of their projects ex-post, reducing their size and thereby completing them faster. This appendix supplements such discussion. First, we provide some institutional details about the construction industry. Second, we elaborate on discussions we had with our data provider on these concerns. Third, we implement robustness checks to our main specifications. Despite data limitations, qualitative and quantitative evidence alleviates concerns that our results are driven by the credit supply shock leading to ex-post changes in project scope.

Construction in India: Institutional Details Construction is a risky endeavor. Perhaps unsurprisingly, there are established legal frameworks to allocate risks between the parties involved in a construction project. Admittedly, many of such contracts are incomplete in the sense of Hart and Moore (1988). Yet, the sheer monetary value associated with many construction projects has led to the emergence of standard contractual forms, which are then adapted to specific situations. In this appendix, we describe some of the contractual features of the modern construction industry and how they buttress our interpretation of the empirical results.

Construction contracts involve two key parties: the sponsor and the contractor. The former wants to build a particular structure, whereas the latter executes the construction. As the project grows in scope, the number of parties can increase substantially, with the addition of architects, engineers, subcontractors, subcontractors to subcontractors, and so on.

The Indian Contract Act of 1872 – largely based on English Common Law – governs construction contracts. According to Indian Accounting Standard 7, a construction contract is any contract "entered into specifically for construction of an asset or a combination of assets that are closely inter-linked or inter-dependent in terms of their design, technology, function, or ultimate purpose".

Construction contracts normally combine multiple documents. First, there are the drawings of the construction work to be done; these are complemented by "specs", which painstaking describe the full scope and quality of the work. Specs can be extremely complex for an engineering perspective (e.g. structural calculations for a suspended bridge) and include detailed instructions of the materials used in the enterprise (e.g. the particular steel beams for the structure of a commercial building) Related to the specs is the bill of quantities, which lists the materials required and normally used to estimate in good faith the project cost. In the language of our model, these engineering primitives are captured by $(\bar{x}, \bar{i})$.

Moving from the technical to the legal aspects, the Conditions allocate responsibilities and risks to each party. The sponsor requirements lists the sponsor's expectations of the contractor, including the scope and quality of the work done. The performance requirements

lists the desired output (e.g. the generating capacity of a power plant or the final square footage of a residential building). Last, there are clauses related to dispute adjudication, which range from voluntary agreement to litigation and termination.

While the construction industry in India does not formally subscribe to a particular standard contract, it is in practice common to adhere to the suite of contracts published by the International Federation of Civil Engineers (FIDIC) or by the Indian Institute of Architects. This is also a common practice, for example, in the US, where most contracts are based off the American Institute of Architects, many of which adapt the frameworks from FIDIC. Among contracts with a private sponsor, the most frequently used FIDIC form is the design-build Contract (often further split into a "design-bid-build" contract).

The key characteristic is the separation of three distinct phases. The first phase is the design phase, when the sponsor engages a design team. The sponsor and the selected design team assume responsibility for all design aspects of the project, including scope and quality standards. In the language of our model, this is the stage at which $(\bar{x}, \bar{\imath})$ are determined. When the design is finished, the sponsor invites contractors to bid for the right to implement the work. The bid phase may involve the selection of single contractor, which then hires additional subcontractors; or the splitting of the works into multiple contractors, each bidding separately for parts of the project. It is quite common for the bid phase to abide to "least-cost" principles, though there remains some discretion on the sponsor to select the contractors. Last, the build phase ensues, in which the contractors implement the design.

While the design-build form gives the sponsor clarity over the design and construction of the asset, it is not without flaws. The separation of design and building often means that inconsistencies may arise between the original plan and the ongoing implementation. If there are no easy remedies for the discrepancies, substantial delays and cost overruns may occur. The design team and the building team may not see eye-to-eye in those disagreements, effectively complicating a swift resolution. Further, there are instances where it's unclear whether the contractual liability lies with the design or the build side of the contract.

At the time of signature, the contract will specify the scope of the project. If the sponsor moves to change to the scope of the project ex post – a "variation in the works" – the contractor must approve the variation and is entitled to compensation for the additional work required. In fact, any term of clause that allowed the sponsor to unilaterally and substantially change the contract by omitting obligations to the contractor would be considered unenforceable in court. Crucially, the variations must be of limited nature. If they substantially alter the contract or if they are not under the contractor's ability to execute, such variations may be denied or result in contractual breaches.

Particular to our setting, variations map into either the adjustment costs $\kappa(\cdot)$ or into the project scope $\bar{x}$. Requesting that the work be accelerated with no changes in scope is a valid variation so long as the contractor is (i) duly compensated for the resulting costs (e.g. in-

creased wage payments for overtime, as captured by additional marginal costs $\kappa'(\cdot)$ in the model) and (ii) the acceleration did not entail impossible deadlines on the contractor. But changing the project ex post to reduce its scope – and therefore reduce the originally contractually stipulated pay to the contractor – can result in legal action against the sponsor, unless explicitly consented by the contract. It is not uncommon for any major negative variation to induce a partial termination of contract, which then likely entails indemnifications from the sponsor to the contractor.

In case disputes arise, arbitration is the usual mechanism for resolutions. Though India is known to be a pro-arbitration jurisdiction with well-established arbitration frameworks, congestion in the legal system and other judicial delays effectively increase the cost of resolving disputes. As a result, negotiations between parties to amend the contract in good faith and mutual consent are often pursued first.

Variations in works are inevitable in construction contracts. Construction if often long-lived and subject to stochastic shocks. Variations give some flexibility for the contractor and the sponsor to jointly adapt to shocks in a dynamic environment. Small changes in fixtures, materials, or work hours may be accommodated with joint agreement across sponsor and employer. However, larger variations can result in exorbitant costs for all involved parties and are thus more rare. Regardless of who initiates a change, whether the change is an increase or decrease in scope, or whether the contract has built-in provisions for small variations, drastic changes in scope are likely to result in partial or full termination, with associated legal quandaries.

Robustness based on Communications with Data Provider Besides gathering institutional know-how about variations in works, we communicated with the data provider about our concerns. The Capex team actively monitors projects for changes in scope. We further asked *"Are there instances where a project might get marked as 'Complete', but the company just reduced the scope of the original project and considered it complete?"*

First, Capex told us that they hardly found any drastic changes in scope across many years in the data. Second, were such drastic changes ever found, Capex followed a very structured logic to record project revisions.

If the change in scope is small, the change is recorded directly in a project's profile. Their example was as follows: suppose the initial announcement for a project stated that the sponsor would build a plant with production capacity of X at a cost C. Before implementation starts, the sponsor revises the plans and reduces capacity to 0.9X and costs fall to 0.95C. Capex will then revise the capacity of the project and add a new row in the cost dataset indicating when the revision in cost was made and what the new cost was.

If the change in scope is large, modifications to the project file would depend on the particular change. A hypothetical situation we were given was a change in the use of the

structure. If the initial plan was to build a shopping mall, but then the type of the project changed to a residual complex, Capex would record a new residential project under the same sponsor, and stall the original shopping mall project.

Perhaps more relevant as a threat to our interpretation of the regression results, we probed specifically about a hypothetical drastic reduction in scope. We asked *"Suppose a company was going to build three factories in a single complex. The company had completed two out of the three plants, but then the company runs out of cash. It decides to kill the third plant, and considers the complex completed only with two factories."* In this case, Capex would proceed in two steps. First, they would revise downwards the capacity and the costs of the original project. Second, they would push the incomplete plant into a separate project and mark it as stalled. Their logic is that a project can be considered completed only if all the subunits comprising the project have been completed.

Our communications with the Capex team motivate a first battery of robustness checks to our results. First, we exclude any projects that have more than one phase or unit. Capex has less granular information on costs and production independence of such projects, as otherwise they would have been coded as independent projects within the same sponsor. Excluding multi-unit projects safeguards against the possibility that reductions in scope such as eliminating one unit out of the originally planned are driving the results on completion hazards. Second, we exclude from our regression all projects that experience downward cost restatements. Such revisions proxy for negative variations. Last, we exclude from our sample all firms that had stalled projects over the sample period. Following the example provided by Capex, a stalled project coinciding with completion of other projects within a firm could indicate a negative variation.

Appendix Table A19 presents the results. Panel A removes multi-unit projects. The results are similar to those reported in Table 2. In Panel B.1, we remove any projects that experience any downward revision in cost over their entire lifecycle. For comparison, Panel B.2 estimates the regressions in the full sample of projects with cost information. The results are similar across both panels, and remain statistically significant in both cases.

Panel C discards any project that was ever stalled during its lifecycle. The point estimates are smaller. While the results appear not to be as statistically significant as before, we would have obtained results with smaller p-values had we used exposure variables that use borrower shares from the pre-shock period, as we did in Appendix Table A8. Therefore, the estimates we present are the most conservative. Last, Panel D excludes all companies that had any projects stalled in our sample period (2013-2019). The point estimates are similar to those in Panel C, but the much smaller sample size increases standard errors and precludes us from claiming the results are significant in some specifications. But again, in unreported results, we confirm the results are statistically significant when we use the alternative exposure variables as in Appendix Table A8.

Table A19: Effects of Firm-Level Credit Supply Shocks on Project Completion Hazards

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Remove Multi-Unit Projects							
Exposure	0.1112***	0.0901***	0.0852***	0.0822***	0.0775***	0.0947***	0.0928***
	(0.0285)	(0.0290)	(0.0291)	(0.0277)	(0.0279)	(0.0297)	(0.0298)
N	90289	90289	90289	90289	90289	85812	85812
Panel B.1: Remove Downward Cost Revisions							
Exposure	0.0872***	0.1075***	0.1030**	0.1023**	0.0981**	0.1068**	0.1065**
	(0.0255)	(0.0410)	(0.0415)	(0.0400)	(0.0403)	(0.0462)	(0.0462)
N	51589	51589	51589	51589	51589	47911	47911
Panel B.2: Remove Projects with Missing Costs							
Exposure	0.0970***	0.0997***	0.0941***	0.0941***	0.0885***	0.1247***	0.1198***
	(0.0261)	(0.0345)	(0.0349)	(0.0329)	(0.0332)	(0.0375)	(0.0376)
N	72958	72336	72336	72958	72958	67968	67968
Panel C: Remove Ever Stalled Projects							
Exposure	0.0982***	0.0570**	0.0542*	0.0516*	0.0487*	0.0651**	0.0639**
	(0.0267)	(0.0279)	(0.0280)	(0.0270)	(0.0272)	(0.0276)	(0.0278)
N	104186	104155	104155	104155	104155	99623	99623
Panel D: Remove Any Companies with Projects Stalled							
Exposure	0.0967***	0.0667*	0.0648*	0.0469	0.0451	0.0737**	0.0740**
	(0.0279)	(0.0370)	(0.0369)	(0.0341)	(0.0341)	(0.0375)	(0.0373)
N	52493	52493	52493	52493	52493	49117	49117
Age Splines	✓	✓	✓	✓	✓	✓	✓
Firm FE		✓	✓	✓	✓	✓	✓
State x Year FE		✓	✓	✓	✓	✓	✓
Sector x Year FE				✓	✓		
Industry x Year FE						✓	✓
Firm Controls			✓		✓		✓

Notes: the table reports PPML estimates of the semi-elasticity of project-level hazards to firm exposure to the Asset Quality Review (see model (1)). The sample consists of projects observed quarterly between 2013-2019. Each panel assesses the robustness of the main estimates to eliminating a particular subset of projects that could have experienced reductions in scope following the credit shock. These subsamples were defined based on communications with the data provider. Firm exposure is defined as the weighted-average of lender exposure, where weights correspond to outstanding loans in the previous year. Coefficient estimates are interpreted as the percent effect on the outcome for a one standard-deviation increase in firm exposure. For example, column (1) reports that moving from a firm with average exposure to a firm with one-standard deviation higher exposure increases the hazard by 11.12%. Age splines refer to cubic splines on a project's age (measured in quarters). Firm controls include sales, sales growth, profitability, debt over equity, book leverage, equity issuances, cash over liquid assets, and debt over EBITDA. All firm controls are winsorized at the 1st and 99th percentile, and then standardized. All firm controls are lagged by one-period. The reduction in sample size from columns (5) to columns (6) and (7) results from separation of additional observations by the more granular industry-by-year fixed effects relative to the sector-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Robustness based on Ex-post Malleability Classifications To further assess the robustness of our estimates, we interview construction industry professionals and parse through construction manuals with the help of LLMs to classify projects as "ex-post malleable". The idea is that changing the scope of the project ex-post is more difficult for some projects. Some of these barriers are technical, while others are regulatory. We identify ex-post malleable projects; and reestimate our main specifications whilst removing such projects.

We consider three metrics of ex-post malleability. First, we consider an industry-based measure. Commercial or residential real estate projects are technically less complex than industrial real estate projects or works of heavy civil engineering like bridges, aqueducts, etc. We thus remove projects that are classified as serving any of the following end-user industries: housing construction, computer software, ITES, business services and consultancy, retail trading, wholesale trading, commercial complexes, hotels and restaurants, education, health services, and tourism. Panel A of Appendix Table A20 reports regression estimates excluding such projects. The results are similar to those obtained in Table 2.

Next, we consider a regulatory-based measure. Using the event-level dataset, we identify projects that ever had an event related to regulatory approvals, such as obtaining environmental clearances or other government licenses, locating in a special economic zone, requiring approval by planning commissions, etc. We then reestimate our regression in this subsample of projects. The idea is that any large changes in scope would trigger additional regulatory burden, potentially derailing the project altogether. As regulatory approvals are granted based on pre-determined plans and conditioned on true-faith implementation of such plans, pursuing large scope revisions with disregard for additional reviews could result in judicial action to halt the project. Overall, such regulatory burden would discourage any changes in project scopes. Panel B reports estimates. The point estimates are larger, but remain significant, excluding the results with industry-time fixed effects. We believe the latter arises as the sharp reduction in sample size coupled with the high-granularity of the industry-time fixed effects compromises our power. But the direction of the point estimates is consistent with our baseline interpretation.

Last, we consider an implementation-based measure. The key idea is that changing the project scope is easier before the project actually starts being implemented, i.e. in the design stage. This logic holds for at least three reasons. First, once construction has started, it often becomes impossible from an engineering standpoint to reduce or increase the scope of the project. For example, one cannot convert a four-lane suspended bridge into a five- or three-lane suspended bridge without threatening the structural soundness of the project. Second, if the project is under a design/build contractual arrangement, changes in scope might require approval of the design firm, which can substantially delay completion. Third, changes in scope midway may induce large variations in costs and schedules, which can trigger partial contractual terminations and follow-on costly arbitration if contractors oppose the changes.

This is even more pronounced for complex projects, where networks of different subcontractors are normally interlocked in the project's execution through contractual chains, thereby increasing the potential for hold-up problems (Hart and Moore 1988). Our implementation-based subsample only keeps projects that were marked as "under implementation" before the AQR shock. Panel C reports results. As in Panel B, the point estimates are larger and remain significant, except for the specifications with industry-time fixed effects. Again, we argue this is an issue of power, not bias.

Taking Stock. This appendix sought to alleviate concerns that our results were driven by firms prematurely completing their projects by suddenly reducing their scope following the shock. A perfect test of this assumption would require us to observe changes in contractual arrangements or in specifications. Unfortunately, these data are not available through CapexDx. We instead relied on a combination of qualitative evidence and robustness checks to diminish such concerns to the best of our abilities and extant data.

First, we argued that contractual structures frequently used in the construction industry do not preclude small variations in works. But such contracts do make ex-post reductions in project scope costly, the more so the larger is the change in scope. The frictions are even more binding for large capital expenditure projects undertaken by sizable sponsors, as in our sample. Second, we repeated our empirical analyses discarding projects who proxied to be most susceptible to potential reductions in scope. Some tests relied on information about how the data provider keeps track of changes in project scopes, while some relied on technological or regulatory aspects of construction that preclude large variations while the project is ongoing. Across these quantitative exercises, we find encouraging evidence that our point estimates remain similar to the baseline results, bolstering our interpretation of the findings.

Table A20: Effects of Firm-Level Credit Supply Shocks on Project Completion Hazards

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A: Remove Malleable			
Exposure	0.0851***	0.0774**	0.0768**	0.0757**	0.0748**	0.0976***	0.0981***
	(0.0269)	(0.0320)	(0.0324)	(0.0322)	(0.0324)	(0.0338)	(0.0340)
N	74483	74439	74439	74439	74439	69960	69960
				Panel B: Some Regulatory Event			
Exposure	0.0789***	0.2180***	0.2193***	0.2186***	0.2182***	0.1650	0.1634
	(0.0258)	(0.0805)	(0.0789)	(0.0799)	(0.0779)	(0.1009)	(0.1006)
N	29966	29966	29966	29966	29966	24765	24765
				Panel C: Under Implementation before Shock			
Exposure	0.1180***	0.1402***	0.1348***	0.1269***	0.1220***	0.0665*	0.0614
	(0.0351)	(0.0388)	(0.0390)	(0.0388)	(0.0391)	(0.0398)	(0.0400)
N	65046	65046	65046	65046	65046	61611	61611
Age Splines	✓	✓	✓	✓	✓	✓	✓
Firm FE		✓	✓	✓	✓	✓	✓
State x Year FE		✓	✓	✓	✓	✓	✓
Sector x Year FE				✓	✓		
Industry x Year FE						✓	✓
Firm Controls			✓		✓		✓

Notes: the table reports PPML estimates of the semi-elasticity of project-level hazards to firm exposure to the Asset Quality Review (see model (1)). The sample consists of projects observed quarterly between 2013-2019. Each panel assesses the robustness of the main estimates to eliminating a particular subset of projects that could have experienced reductions in scope following the credit shock. These subsamples were defined based on our conversations with practitioners and LLM parsing of construction manuals. Firm exposure is defined as the weighted-average of lender exposure, where weights correspond to outstanding loans in the previous year. Coefficient estimates are interpreted as the percent effect on the outcome for a one standard-deviation increase in firm exposure. For example, column (1) reports that moving from a firm with average exposure to a firm with one-standard deviation higher exposure increases the hazard by 8.51%. Age splines refer to cubic splines on a project's age (measured in quarters). Firm controls include sales, sales growth, profitability, debt over equity, book leverage, equity issuances, cash over liquid assets, and debt over EBITDA. All firm controls are winsorized at the 1st and 99th percentile, and then standardized. All firm controls are lagged by one-period. The reduction in sample size from columns (5) to columns (6) and (7) results from separation of additional observations by the more granular industry-by-year fixed effects relative to the sector-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

F Narrative Examples of Endogenous Time to Build

This appendix elaborates on our reading of corporate transcripts. We collected corporate call transcripts from LSEG Refinitiv Transcripts (Hassan et al 2025). We restrict to Indian firms pre FY2020 that we could merge to our . Reading through all 3,000 or so resulting transcripts was unfeasible, so we identified instances where words related to (i) acceleration, (ii) projects, and (iii) finance co-located within 200 tokens;[57] and then read the resulting subset.[58] Though we cannot replicate full excerpts, a few quotes provide narratives consistent with endogenous time-to-build, and some mention faster cash flow generation as a by-product of expediting projects:

- Tata Steel, FY 2013: "Our focus as a management team is actually to accelerate and see how we can implement Orissa on time and on cost despite the challenges associated with greenfield projects"
- Godrej Properties, FY 2016: "We are just days away from delivering this project ahead of schedule and are confident of monetizing the entire project within the current financial year. We expect approximately INR1,500 crore of net positive cash flow from this project in the quarter"
- Power Finance Corporation, Q3 2017: "62% of INR10,660 crores are projects under implementation, where we are in discussion with various vendor, exploring options to expedite commissioning."
- Puravankara Ltd, Q3 2017: "This is over and above the standing instruction for repayment of debt, which is linked to the acceleration of our sales of completed and nearly completed inventory"

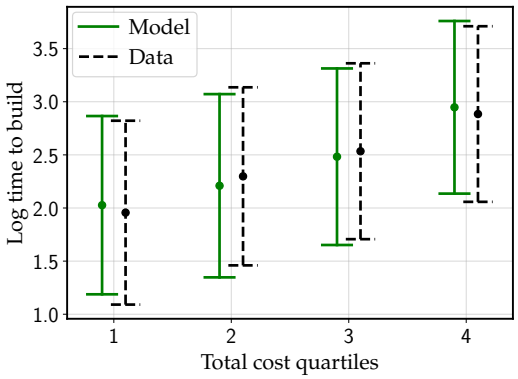
These quotes exemplify how firms discuss project timelines and expedited completion. Importantly, they are not systematic narrative evidence, which is beyond the scope of this paper. Our main econometric evidence is our quasi-experimental hazard estimates.

[57] The bag of words for each topic were "accelerat | fast[-]track | expedit | prepon | | bring forward | pull forward | speed.? up" for acceleration; "construct | build | comission | milestone | cwip | work[-]in[-]progress | deliver | hand[-]over | project | plant | facility | capex | factory | complet | finish" for prrojects; and "cash ?flow | liquidit | working capital | refinanc | cost of capital | interest rate | interest cost | bank | asset quality | NPA | non[-]performing" for finance.

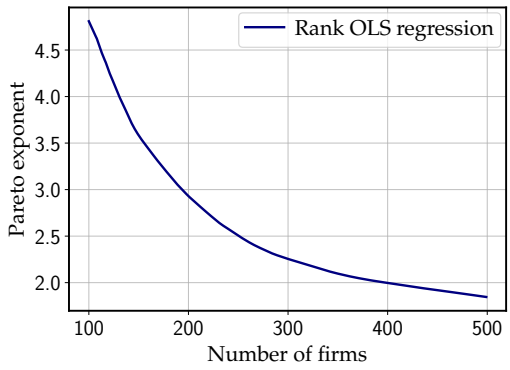
[58] The "hit rate" was low, reflecting the prevalence of generic sentences such as "we expect cash flows to accelerate in coming quarters". This highlights the importance of manually reading a few transcripts to avoid false positives. Consistent with this low hit-rate for high-specificity corporate jargon, Gormsen and Huber (2025) and Selgrad and Siani (2025) manually read through paragraphs of corporate transcripts to detect when firms talk about their discount rates and capex plans, respectively. Managers are selective when disclosing project details. In our reading, many of the transcripts that mentioned project timelines did so precisely when pressed by an analyst.

G Additional Quantitative Results

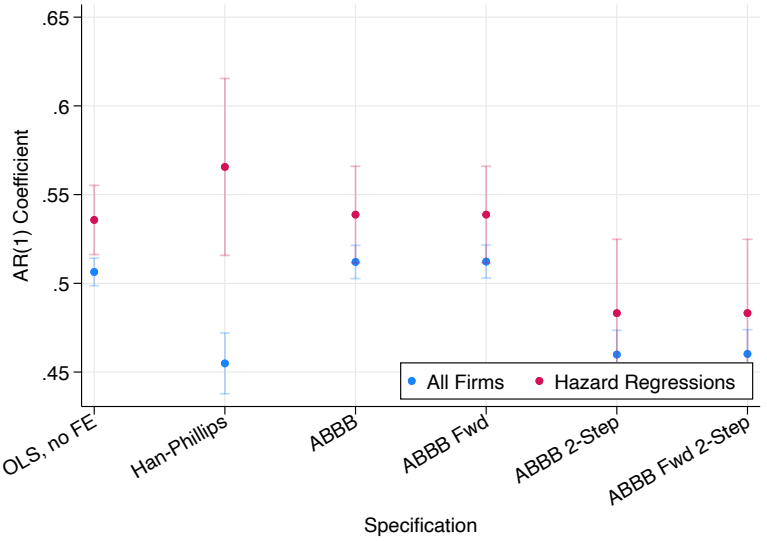
Figure A20: Calibration Exercises



(a) Project Size and Time to Build



(b) Project Output



(c) Shock Persistence

Notes: The figure plots the results of our calibration exercises. Subfigure A20a plots the joint distribution of costs and time to build in the model (green, solid) and in the data (black, dashed). We leverage such moments to calibrate the parameters related to the distributions of $\bar{x}$ and $\bar{i}$. Subfigure A20b plots the results from estimating log-rank regressions. The x-axis plots the number of (top) firms included in the estimation. The y-axis plots the resulting coefficient of a regression of log sales on firm rank, which corresponds to an estimate of the Pareto exponent. We choose a midpoint of 3. Subfigure A20c plots coefficient estimates of multiple panel autoregressive models used to estimate the persistence of the discount rate shock ρ. We regress firm exposure on its first lag, clustering at the firm level. Each bin in the x-axis corresponds to a distinct estimator. From left to right, we report estimates from OLS without fixed effects, the Han-Phillips GMM estimator, and multiple variations of the Arellano-Bover-Blundell-Bond system GMM estimator ("Fwd" indicates taking forward deviations, and "2-Step" indicates use of two-step GMM with optimal covariance matrix). Blue dots plot estimates (and 95% confidence bands) in the sample of all firm-years in the MCA-Prowess matched data. Red dots restrict the sample to firms in our hazard regressions.

Table A21: Calibration Results: Parameter Estimates

Parameter	Value	Interpretation	Source
r	0.01	Real Rate	Post-1990 Time Series Average
p	1	Price of K	Normalization
$\mu_{\bar{x}}$	0	Avg Project Size	
$\sigma^2_{\bar{x}}$	2.12	SD Project Size	
$\beta^{\bar{i}}_0$	-2.47	Mean $\bar{i}$: intercept	Cost-TTB Distribution
$\beta^{\bar{i}}_1$	0.82	Mean $\bar{i}$: slope	
$\sigma^2_{\bar{i}}$	0.88	SD $\bar{i}$	
ρ	0.17	Shock Persistence	Panel Autoregressions
α	3	Pareto Tail	Log-Rank Regressions
s	0.02	Shock Size	Reduced Form Regressions
κ	3.09	Accel. Cost	

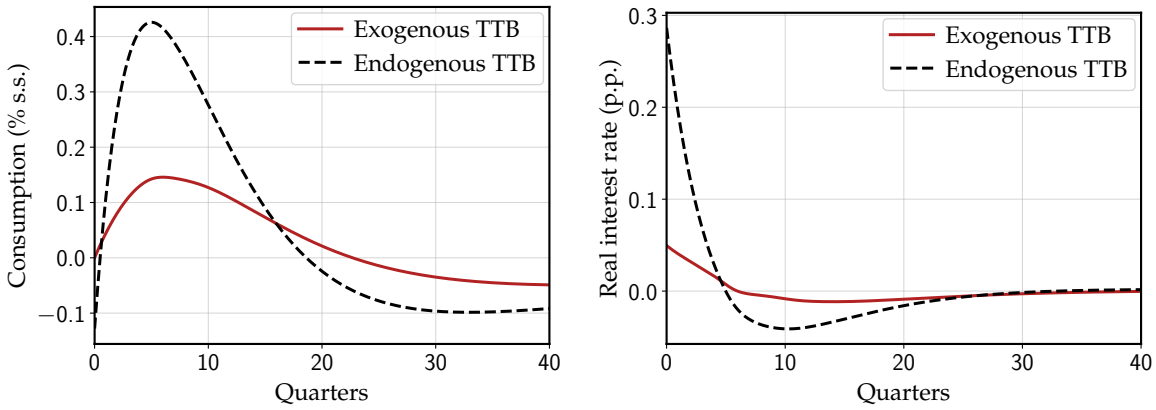
Notes: the table reports parameter estimates from our calibration exercise. See the notes to figure A20 and the main text for detailed explanations of the calibration strategy.

Table A22: Calibration Results: Targeted Moments

Moment	Model	Data
Avg Log Size (Q1)	-2.68	-2.58
Avg Log Size (Q2)	-1.42	-1.57
Avg Log Size (Q3)	0.01	-0.18
Avg Log Size (Q4)	1.45	1.42
Avg Log Size (Q5)	2.77	2.80
SD Log Size	0.91	0.90
Avg Log TTB (Q1)	1.96	2.02
Avg Log TTB (Q2)	2.30	2.21
Avg Log TTB (Q3)	2.53	2.48
Avg Log TTB (Q4)	2.88	2.95
Hazard Regression β	0.06	0.06
Starts Regression β	-0.08	-0.08

Notes: the table reports values for the targeted moments in our calibration exercise. See the notes to figure A20 and the main text for detailed explanations of the calibration strategy.

Figure A22: IRFs of consumption and interest rates to discount rate shock in GE.



(a) Consumption

(b) Interest Rates

Note: the figure plots (quarterly) impulse response functions (IRFs) of aggregate consumption (panel a) and discount rates (panel b) in discount rates in general equilibrium. The y-axis measures percent-deviations from steady state values. Shock persistence, shock size, and remaining parameters as in appendix table A21.

H Proofs and Additional Theoretical Results

H.1 Time to Completion and the Kolmogorov Backward Equation

Let $T(x,t)$ denote the time remaining until completion for a project in stage x at time t. In a time span Δt, to first-order, we have

$$T(x,t) \approx \Delta t + T(x + i(x)\Delta t, t + \Delta t)$$

Rearranging, we obtain

$$0 \approx 1 + \frac{T(x + i(x)\Delta t, t + \Delta t) - T(x,t)}{\Delta t}$$

For $i(x)\Delta t$ small,

$$T(x + i(x)\Delta t, t + \Delta t) \approx T(x, t + \Delta t) + i(x)\Delta t \frac{\partial}{\partial x} T(x,t)$$

Note further that

$$\frac{T(x, t + \Delta t) - T(x,t)}{\Delta t} \to \frac{\partial}{\partial t} T(x,t)$$

Hence, as $\Delta t \to 0$, we obtain a Kolmogorov Backward Equation

$$0 = 1 + i(x,t)\frac{\partial}{\partial x} T(x,t) + \frac{\partial}{\partial t} T(x,t) \tag{20}$$

with terminal condition

$$T(\overline{x}, t) = 0 \tag{21}$$

In steady state, we have $\frac{\partial}{\partial t} T(x,t) = 0$, which yields the $T'(x) = -1/i(x)$.

Proposition 8. *In steady state, completion times are uniformly distributed.*

Proof. The distribution of completion times is

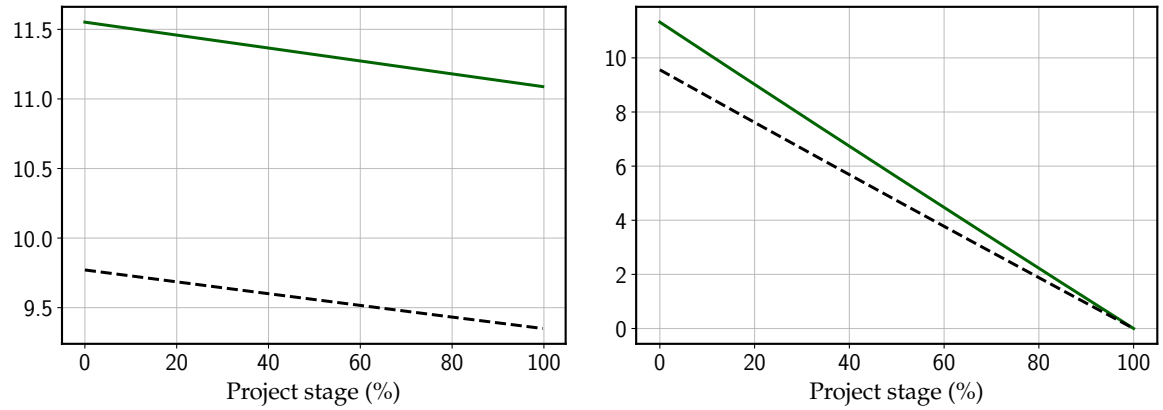
$$F_T(t) = \text{Prob}(T(x) \leq t) = \int_{T^{-1}(t)}^{\bar{x}} g(x)dx$$

i.e. the mass of projects being completed up to time t is just the mass of projects about to be completed (close to $\bar{x}$) down to projects in stages such that after t periods, the project will be completed. Note that $g(x)$ does not integrate to 1, but this is not a serious concern.

Using Leibniz's rule, we differentiate the cumulative to obtain the density

$$f_T(t) = -g(T^{-1}(t)) \times (T^{-1})'(t)$$

Figure A22: Steady state objects as functions of project stage



(a) Stationary distribution $g(x,z)/f(z)$ (b) Time until completion $T(x,z)$

Note: the figures plot the steady state solution of the model. Panel (a) plots the stationary distribution $g(x,z)/f(z)$, and panel (b) plots the time to completion distribution $T(x,z)$. The x-axis is the project stage, defined as $100 \times x/\bar{x}$. Solid green lines represent low output projects ($z = 2$); black dashed lines represent high output projects ($z = 8$). Parameters are set at the median values obtained in our calibration in section 5: $r = 0.01$, $p = 1$, $\bar{x} = 1$, $\bar{i} = 0.083$, $\kappa = 30.1$.

Recall that the derivative of the inverse function is given by

$$(T^{-1})'(t) = \frac{1}{T'(T^{-1}(t))},$$

but $T'(x) = -1/i(x)$ and $g(x) = f/i(x)$, so for $x = T^{-1}(t)$, we obtain

$$\begin{aligned} f_T(t) &= \left(-\frac{f}{i(T^{-1}(t))}\right) \times \left(-\frac{1}{1/i(T^{-1}(t))}\right) \\ &= f \end{aligned}$$

Figure A22 shows the stationary distribution (normalized by project size) and the time to completion as a function of the project stage. Panel (a) shows the stationary distribution normalized by the flow of entrants, $g(x,z)/f(z)$, which is simply $1/i(x,z)$. There is a larger mass of active projects, given by the area below the curve, for lower values of z (relative to the flow of entrants $f(z)$), reflecting the fact that projects with lower z take longer to be completed. Panel (b) shows the time until completion $T(x,z)$, which is higher for low-productivity projects until reaching zero at $x = \bar{x}$.

□

H.2 First-Order Dynamics: Terminal Payoff Shocks

In the main text, we restricted attention to the first-order dynamics of the value function and of investment following a AR(1) shock to discount rates. It is feasible (and easier) to derive similar dynamics in the case of a shock to the terminal payoff of the project, i.e. a shock of the form

$$p(t) = p(1 + se^{-\rho t})$$

We leverage the results from Lemma 1, which generalizes straightforwardly to p-shocks. With a slight abuse of notation, we again use "hatted", lower-case variables to denote the partial derivatives of a function with respect to the shock size s, evaluated at the steady state.

Proposition 9. *The first order response of project value to a AR(1) shock to terminal payoff is given by*

$$\hat{v}(x, z) = pze^{-(r+\rho)T(x,z)}, \tag{22}$$

and the first order response of investment flows to the same shock is given by

$$\hat{i}(x, z) = \frac{1}{\kappa''(i(x, z))} \frac{\partial \hat{v}(x, z)}{\partial x} \tag{23}$$

Proof. The time-dependent HJB is given by

$$r\mathcal{V}(x, z, s, t) = -\mathcal{I}(x, z, t, s) - \kappa(\mathcal{I}(x, z, t, s)) + \mathcal{I}(x, z, t, s)\frac{\partial}{\partial x}\mathcal{V}(x, z, t, s) + \frac{\partial}{\partial t}\mathcal{V}(x, z, t, s)$$

with terminal condition

$$\mathcal{V}(\bar{x}, z, s, t) = pz(1 + se^{-\rho t})$$

and where $\mathcal{I}(x, t, s)$ solves

$$1 + \kappa'(\mathcal{I}(x, z, t, s)) = \frac{\partial}{\partial x}\mathcal{V}(x, z, t, s)$$

Differentiate the HJB and the terminal condition with respect to s using the Envelope Theorem

$$r\frac{\partial}{\partial s}\mathcal{V}(x, z, s, t) = \mathcal{I}(x, z, t, s)\frac{\partial}{\partial s}\frac{\partial}{\partial x}\mathcal{V}(x, t, s) + \frac{\partial}{\partial s}\frac{\partial}{\partial t}\mathcal{V}(x, z, t, s)$$

$$\frac{\partial}{\partial s}\mathcal{V}(\bar{x}, z, s, t) = pze^{-\rho t}$$

Define the steady-state gradients

$$\hat{v}(x, z, t) := \frac{\partial}{\partial s}\mathcal{V}(x, z, s, t)\Big|_{s=0}$$

and evaluate the HJB at the steady state, after switching the order of differentiation

$$r\hat{v}(x,z,t) = i(x,z)\frac{\partial}{\partial x}\hat{v}(x,z,t) + \frac{\partial}{\partial t}\hat{v}(x,z,t)$$

Define $\hat{v}(x,z) \coloneqq \frac{\partial}{\partial s}\mathcal{V}(x,z,s,t)\Big|_{s,t=0}$ and conjecture $\hat{v}(x,z,t) = e^{-\rho t}\hat{v}(x,z)$. Then, the HJB becomes

$$(r+\rho)\hat{v}(x,z) = i(x,z)\frac{\partial}{\partial x}\hat{v}(x,z)$$

which is an ODE on $\hat{v}(x,z)$ with terminal condition $\hat{v}(\overline{x}) = pz$. Recalling $\partial T(x,z)/\partial x = -1/i(x,z)$ in steady state, we can solve the ODE subject to the terminal condition and obtain (22).

Moving towards investment, differentiate the FOC with respect to s

$$\kappa''(\mathcal{I}(x,z,t,s))\frac{\partial}{\partial s}\mathcal{I}(x,z,t,s) = \frac{\partial}{\partial s}\frac{\partial}{\partial x}\mathcal{V}(x,z,t,s)$$

Switching the order of differentiation and evaluating at a steady state, we obtain

$$\kappa''(i(x,z))\hat{i}(x,z,t) = \frac{\partial}{\partial x}\hat{v}(x,z,t)$$

where we defined $\hat{i}(x,z,t) \coloneqq \frac{\partial}{\partial s}\mathcal{I}(x,z,s,t)\Big|_{s=0}$. Once again, we conjecture $\hat{i}(x,z,t) = e^{-\rho t}\hat{i}(x,z)$ (and analogously for $\hat{v}(x,z,t)$), where as before $\hat{i}(x,z) \coloneqq \frac{\partial}{\partial s}\mathcal{I}(x,z,s,t)\Big|_{s,t=0}$. Cancelling the exponential term, we readily obtain (23). □

Proposition 9 states that we can obtain a sense of the change in project value simply by discounting the terminal payoff. If the terminal payoff rises (falls), value rises (falls). The actual insight of the proposition is to tell us the correct discount factor and the correct time length for the discounting exercise. Since the shock in the terminal payoff is persistent, the discount rate rises from r to $r+\rho$. In the limit of a permanent change in terminal payoffs, the discount rate is just r. When $\rho < 1$, the shock is temporary, so we raise the discount factor to account for the fading dynamics.

Most crucially, we relevant time frame for discounting is just given by the steady state remaining time to build $T(x,z)$. Fledgling projects respond *less* to price shocks relative to mature projects. For any fixed discount rate, their terminal cash flows are far away. Discounting pushes their value downwards. Unless the shock is very persistent, it is unlikely that the firm will be able to capture the benefits of the shock. Granted, since our shock is a AR(1) shock, it only completely dies out in the limit of $t \to \infty$, so even projects that have just been started still have some reaction to the shock. But the benefits that will accrue to such young projects are smaller, for it will take longer to reach completion.

Turning to the second result of Proposition 9, we find that investment rises (falls) follow-

ing a positive (negative) shock to terminal payoffs – the acceleration costs are assumed to be convex and $\frac{\partial}{\partial x}\hat{v}(x,z) > 0$. In the case where κ is quadratic, as in our quantitative exercises, the model makes an unconditional prediction that investment in more mature projects reacts more to shocks to terminal payoffs. The intuition falls off from the result that such mature projects have greater changes in value following the shock. When convexity depends on the level of investment, whether such monotonicity on project stage holds relies on quantitative exploration. Since steady state investment is increasing in project stage, the total effect depends on the relative magnitudes of valuation gains versus acceleration costs, both of which become increasing in project stage.

Last, we turn to the extensive margin. Proposition 10 shows that a positive terminal payoff shock lowers the entry threshold and therefore boosts project starts, consistent with standard investment theory.

Proposition 10. *The first-order response of the entry threshold $\bar{z}$ to an AR(1) terminal payoff shock is given by*

$$\hat{z} = -\bar{z}e^{-\rho T(0,\bar{z})} \tag{24}$$

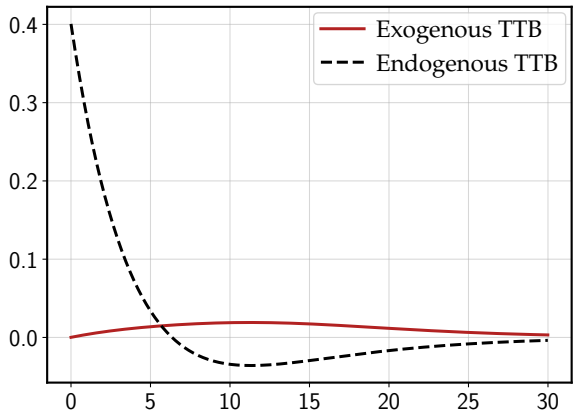
Proof. We can follow the same steps as in the proof of Proposition 5. Using (22) and (35), we find

$$\begin{aligned}\hat{z} = \frac{\partial \bar{z}}{\partial s} &:= -\frac{\partial v(x,z)/\partial x}{\partial v(x,z)/\partial z}\bigg|_{(x,z)=(0,\bar{z})} \\ &= -\frac{p\bar{z}e^{-(r+\rho)T(0,\bar{z})}}{pe^{-rT(0,\bar{z})}} = -\bar{z}e^{-\rho T(0,\bar{z})}\end{aligned}$$

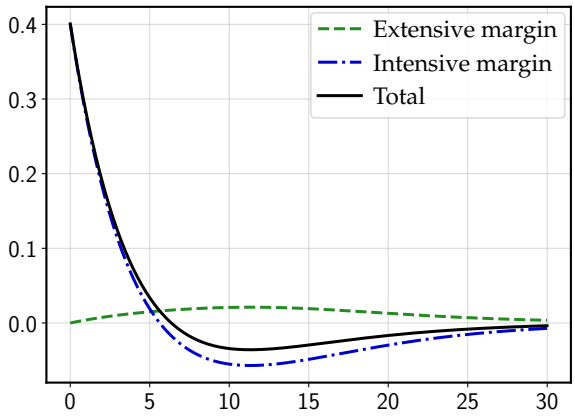
□

Figure A22 illustrates our analytical results using our quantitative model. We consider a AR(1) perfect-foresight increase in terminal payoffs p, holding fixed discount rates. One can interpret the price shock, for example, as a productivity shock under a competitive market structure and constant returns to scale. In the exogenous world, the effect is strictly positive, as the positive payoff shock raises entry. In the endogenous world, there is a short-run spike in investment: firms rush to complete projects while returns are higher. As projects are completed, the distribution skews to earlier-stage projects with smaller steady state investment. The intensive margin effect thus drops below zero, until it converges back to steady state. The resulting effect is a short-run boom followed by a long-lived mild slump.

Figure A22: Impulse response functions of investment to price shock.



(a) Total IRF for endogenous versus exogenous time to build model



(b) Decomposition of endogenous time to build IRF between intensive and extensive margins

Note: the figure plots (quarterly) impulse response functions (IRFs) of aggregate investment to a price shock in partial equilibrium (i.e. fixing r to its steady state level following the shock). The y-axis measures percent-deviations from steady state values. Panel (a) plots the IRFs for the exogenous time to build model (red solid line) and for the endogenous time to build model (black dashed line). Panel (b) decomposes the total IRF (black solid line) from the endogenous time to build model into the extensive margin (green dashed line) and the intensive margin (blue dot-dashed line). Shock persistence, shock size, and remaining parameters as in appendix table A21.

H.3 Endogenous p

In our baseline model, we restricted attention to an exogenous terminal payoff pz. This is consistent with the benchmark neoclassical framework with frictionless rental markets or secondary markets for capital resales. We can also think of p as a contractually stipulated payoff that cannot be renegotiated. This meant that p was independent of changes in r. We now relax this assumption and show that our main analytical results still hold.

If the plant must be operated after construction, the cash flows accruing to the project after its completion should also respond to changes in discount rates. Suppose that the completed project depreciates at a constant rate $\delta > 0$ and generates exogenous cash flows $c > 0$. The present value of operating the project is given by

$$p(t) = \int_t^\infty c e^{\int_t^\tau (r(u)+\delta)du} d\tau$$

so that $p = {}^{c}/_{(r+\delta)}$ in steady state. We normalize cash flows c such that, for any price p and steady state discount rate r, we have $c = p(r+\delta)$.

Consider again a perfect foresight, AR(1) discount rate shock $r(t) = r + se^{-\rho t}$. The following lemma computes the change in $p(t)$ resulting from this shock.

Lemma 11. *The first-order response of the present value of operating the project is given by*

$$\frac{\hat{p}(t)}{p} = -\frac{e^{-\rho t}}{r+\delta+\rho} \tag{25}$$

Proof. After the interest rate shock,

$$\begin{aligned} p(t) &= c\int_t^\infty \exp\left[-\left(r+\delta+s\int_t^\tau e^{-\rho u}du\right)\right]d\tau \\ &= c\int_t^\infty \exp\left[-\left(r+\delta+s\frac{1}{\rho}(e^{-\rho t}-e^{-\rho\tau})\right)\right]d\tau \end{aligned}$$

Taking the derivative with respect to s and evaluating at $s=0$, we obtain

$$\begin{aligned} \hat{p}(t) &= -c\int_t^\infty \frac{1}{\rho}(e^{-\rho t}-e^{-\rho\tau})e^{-(r+\delta)(\tau-t)}d\tau \\ &= -\frac{c}{\rho}e^{-\rho t}\int_t^\infty \left(e^{-(r+\delta)(\tau-t)}-e^{-(r+\delta+\rho)(\tau-t)}\right)d\tau \\ &= -\frac{c}{\rho}e^{-\rho t}\left(\frac{1}{r+\delta}-\frac{1}{r+\delta+\rho}\right) \\ &= -\underbrace{\frac{c}{(r+\delta)}}_{=p}\frac{e^{-\rho t}}{(r+\delta+\rho)} \end{aligned}$$

□

With this result, we can extend 3 to the case where p depends directly on r

Proposition 12. *The first order response of the optimal investment policy is given by*

$$\hat{i}(x,z) = \frac{1}{i(x,z)\cdot\kappa''(i(x,z))}\cdot\left[\underbrace{v(x,z)+(r+\rho)\hat{v}(x,z)}_{\text{Fixed } p} - \underbrace{\frac{r+\rho}{r+\delta+\rho}e^{-(r+\rho)T(x)}pz}_{\text{Price Response}}\right], \tag{26}$$

Proof. As p now depends on r, we have, by the chain rule,

$$\hat{i}(x,z) = \hat{i}_r(x,z) + \hat{i}_p(x,z)\cdot\hat{p}$$

We have already computed all these derivatives. First, $\hat{i}_r(x,z)$ is the response of investment with respect to r keeping p fixed, which is given by (14) and (15) in Proposition 3. Second,

$\hat{i}_p(x,z)$ is the response of investment with respect to p keeping r fixed, which is given by (23) in Proposition 9. Last, $\hat{p}$ is given by (25) in Lemma 11. Substituting all expressions and simplifying yields the result. □

Expression 26 is composed of two terms. The first, "Fixed p", is the marginal value of accelerating the project, or reducing the project's duration, in the case where p is independent of r, i.e. 15. The second, "Price Response", captures the change in the value of operating the project due to changes in the discount rate. As discounting rises, future cash flows are less valuable, which reduces the incentives to complete the project and therefore pushes towards delaying project completion. Even with these headwinds, we can still prove that acceleration is optimal for projects sufficiently close to completion.

Corollary 13. *For x sufficiently close to $\bar{x}$, we have*

$$\lim_{x\to\bar{x}} \hat{i}(x,z) = \frac{1}{i(\bar{x},z)\cdot\kappa''(i(\bar{x},z))}\frac{\delta}{r+\delta+\rho}pz > 0 \tag{27}$$

Proof. Note that $T(x) \to 0$ as $x \to \bar{x}$. From the proof of Corollary 4, we know $\hat{v}(x,z) \to 0$ and $v(x,z) \to pz$. Simplifying yields the result. □

Therefore, when discount rates rise, it remains optimal to accelerate the pace of completion for projects sufficiently close to completion, *so long as the project depreciates at a positive rate*. The incentives to accelerate shrink, however, by a factor $\delta/r+\rho+\delta \in (0,1)$.

H.4 Risk

This section introduces risk into the endogenous time to build model from the main text, with the objective of understanding how this affects our main theoretical results. We find that introducing risk related to the value of a finished project does not affect the result that firms accelerate projects close to completion following an increase in their discount factor. More generally, we show that risk does not affect investment behavior close to completion.

Suppose that the project productivity z_t is now time-varying and now follows a Poisson process. Let $z_1 < \cdots < z_J$ be the possible values for z_t and μ_{jk} be the rate at which a jump occurs from state z_j to state z_k, i.e.,

$$Prob(z_{t+\Delta} = z_k | z_t = z_j) = \mu_{jk}\Delta + o(\Delta).$$

The optimization problem of firms is now characterized by a set of value functions $V_j(x)$, corresponding to the value of having a project at stage x and productivity z_j, given by

$$r(t)V_j(x,t) = \max_{i\geq 0} -i - \kappa(i) + \frac{\partial V_j(x,t)}{\partial x}i + \frac{\partial V_j(x,t)}{\partial t} + \sum_{k\neq j}\mu_{jk}\left[V_k(x,t) - V_j(x,t)\right].$$

The terminal condition is now

$$V_j(\bar{x}, t) = pz_j.$$

Importantly, we assume that all firms immediately sell their projects upon completion. This rules out the possibility that a firm completes with very low productivity and then wait for its value to increase before selling it. Optimal investment is characterized by the first order condition:

$$1 + \kappa'(i_j(x,t)) = \frac{\partial V_j(x,t)}{\partial x}.$$

Now suppose, as in the main text, there is an exponentially decaying shock to firms' discount factor:

$$r(t) = r + se^{-\rho t}.$$

As in the case without risk, let variables with hats denote first-order perturbations relative to steady state. The derivation of results here follows the same step as that in the model from the main text. We plug the time-varying discount rate into the HJB equation, take derivatives with respect to shock size s, and guess that $\hat{V}_j$ has the form $\hat{V}_j(x,t) = e^{-\rho t}\hat{V}_j(x)$ to obtain

$$(r+\rho)\,\hat{V}_j(x) + V_j(x) = i_j(x)\hat{V}_j'(x) + \sum_k \mu_{jk}\left(\hat{V}_k(x) - \hat{V}_j(x)\right),$$

$$\hat{V}_j(\bar{x}) = 0.$$

By defining $\mathcal{I}(x) = \text{diag}(i_1(x), \cdots, i_J(x))$, $\tilde{\mu}_j = \sum_{k \neq j} \mu_{jk}$ and

$$\mathcal{Q} = \begin{bmatrix} -\tilde{\mu_1} & \cdots & \mu_{1j} & \cdots & \mu_{1J} \\ \vdots & & \vdots & & \vdots \\ \mu_{j1} & \cdots & -\tilde{\mu}_j & \cdots & \mu_{jJ} \\ \vdots & & \vdots & & \vdots \\ \mu_{J1} & \cdots & \mu_{Jj} & \cdots & -\tilde{\mu_J} \end{bmatrix},$$

this equation can be written as

$$((r+\rho)I - \mathcal{Q})\,\hat{\mathbf{V}}(x) + \mathbf{V}(x) = \mathcal{I}(x)\hat{\mathbf{V}}'(x). \tag{28}$$

Above, $\mathbf{V} = (V_1(x), \ldots, V_J(x))'$, and $\hat{\mathbf{V}}$ and $\hat{\mathbf{V}}'$ are defined similarly.

To solve equation 28, consider first the matrix $\Psi(x)$ that solves the homogeneous system

$$((r+\rho)I - \mathcal{Q})\,\Psi(x) = \mathcal{I}(x)\Psi'(x).$$

$\Psi(x)$ is more precisely defined as a matrix whose columns consist of the K linearly indepen-

dent solutions of the homogeneous equations above. We can express $\hat{\mathbf{V}}(x)$ as

$$\hat{\mathbf{V}}(x) = \Psi(x) \int_x^{\bar{x}} \Psi(y)\mathcal{I}^{-1}(y)\mathbf{V}(y)dy,$$

which can be easily checked to satisfy the terminal condition $\hat{\mathbf{V}}(\bar{x}) = 0$.

Having solved for $\hat{\mathbf{V}}(x)$, define $\hat{\mathbf{I}}(x) = (\hat{i}_1(x), \ldots, \hat{i}_K(x))'$. Start from

$$\hat{i}_j(x) = \frac{1}{\kappa''(i_j(x))}\hat{V}_j'(x)$$

and use 28 to obtain

$$\hat{\mathbf{I}}(x) = \mathcal{I}_\kappa^{-1}\left[((r+\rho)I - \mathcal{Q})\,\hat{\mathbf{V}}(x) + \mathbf{V}(x)\right],$$

where $\mathcal{I}_\kappa = \text{diag}\,(i_1(x)\kappa_1''(i_1(x)), \ldots, i_K(x)\kappa_K''(i_K(x)))$. It is straightforward to see that, for x close enough to $\bar{x}$, each entry of $\hat{\mathbf{I}}(x)$ will be positive given that $\mathbf{V}(\bar{x})$ is component-wise positive and $\kappa'' > 0$. Hence, firms will optimally decide to speed up projects close enough to completion even in a setting with risk. More generally, since $\hat{\mathbf{V}}(\bar{x}) = 0$, risk will not influence optimal investment decisions for projects close to completion. The intuition is simple: when projects are sufficiently close to completion, the project behaves as if it is en route to deterministic completion, so that the role of risk vanishes.

H.5 Proofs from Main Text

H.5.1 Proof of Lemma 1 and Proposition 2

We omit z from the derivations to lighten notation. The results hold pointwise along the distribution of z.

Step 1. Linearizing the HJB (Proof of Lemma 1) The time-dependent HJB is given by

$$(r + se^{-\rho t})\mathcal{V}(x,s,t) = -\mathcal{I}(x,t,s) - \kappa(\mathcal{I}(x,t,s)) + \mathcal{I}(x,t,s)\frac{\partial}{\partial x}\mathcal{V}(x,t,s) + \frac{\partial}{\partial t}\mathcal{V}(x,t,s)$$

with terminal condition

$$\mathcal{V}(\bar{x},s,t) = pz$$

and where $\mathcal{I}(x,t,s)$ solves

$$1 + \kappa'(\mathcal{I}(x,t,s)) = \frac{\partial}{\partial x}\mathcal{V}(x,t,s)$$

Differentiate the time-dependent HJB with respect to the shock size s

$$\begin{aligned} r\frac{\partial}{\partial s}\mathcal{V}(x,s,t) + e^{-\rho t}\mathcal{V}(x,s,t) = &- \left(1+\kappa'(\mathcal{I}(x,t,s))\right)\frac{\partial}{\partial s}\mathcal{I}(x,s,t) \\ &+ \frac{\partial}{\partial s}\mathcal{I}(x,s,t)\cdot\frac{\partial}{\partial x}\mathcal{V}(x,t,s) \\ &+ \mathcal{I}(x,t,s)\frac{\partial}{\partial s}\frac{\partial}{\partial x}\mathcal{V}(x,t,s) + \frac{\partial}{\partial s}\frac{\partial}{\partial t}\mathcal{V}(x,t,s) \end{aligned}$$

and from the FOC, a standard Envelope condition arises, yielding

$$r\frac{\partial}{\partial s}\mathcal{V}(x,s,t) + e^{-\rho t}\mathcal{V}(x,s,t) = \mathcal{I}(x,t,s)\frac{\partial}{\partial x}\frac{\partial}{\partial s}\mathcal{V}(x,t,s) + \frac{\partial}{\partial t}\frac{\partial}{\partial s}\mathcal{V}(x,t,s) \tag{29}$$

where we switched the order of differentiation in the last terms.

We define the steady-state gradients

$$\hat{v}(x,t) \coloneqq \frac{\partial}{\partial s}\mathcal{V}(x,s,t)\Big|_{s=0}$$

so evaluating (29) at the steady state,

$$r\hat{v}(x,t) + e^{-\rho t}v(x) = i(x)\frac{\partial}{\partial x}\hat{v}(x,t) + \frac{\partial}{\partial t}\hat{v}(x,t)$$

where $v(x)$ and $i(x)$ are the steady state value and policy functions, respectively.

We conjecture

$$\begin{aligned} \hat{v}(x,t) &= e^{-\rho t}\hat{v}(x) \\ \hat{v}(x) &\coloneqq \frac{\partial}{\partial s}\mathcal{V}(x,s,t)\Big|_{s=0,t=0} \end{aligned}$$

so that

$$re^{-\rho t}\hat{v}(x) + e^{-\rho t}v(x) = i(x)e^{-\rho t}\frac{d}{dx}\hat{v}(x) - \rho e^{-\rho t}\hat{v}(x)$$

Cancelling the $e^{-\rho t}$ terms and rearranging, we obtain

$$(r+\rho)\hat{v}(x) + v(x) = i(x)\frac{d}{dx}\hat{v}(x)$$

Differentiating the terminal condition with respect to s gives us

$$\frac{\partial}{\partial s}\mathcal{V}(\bar{x},s,t) = 0$$

Evaluating at the steady state yields

$$\hat{v}(\bar{x}, t) = 0$$

and given our conjecture, we obtain

$$\hat{v}(\bar{x}) = 0$$

Hence, we obtain an ordinary differential equation in $\hat{v}(x)$ with associated terminal condition

$$\begin{aligned} (r+\rho)\hat{v}(x) + v(x) &= i(x)\frac{d}{dx}\hat{v}(x) \\ \hat{v}(\overline{x}) &= 0 \end{aligned} \tag{30}$$

Step 2. Solving the ODE for $\hat{v}(x)$ We rearrange (30) to obtain

$$\frac{d}{dx}\hat{v}(x) - \frac{r+\rho}{i(x)}\hat{v}(x) = \frac{1}{i(x)}v(x)$$

Multiplying by the integrating factor $e^{(r+\rho)T(x)}$, we have

$$e^{(r+\rho)T(x)}\frac{d}{dx}\hat{v}(x) - \frac{r+\rho}{i(x)}e^{(r+\rho)T(x)}\hat{v}(x) = \frac{e^{(r+\rho)T(x)}}{i(x)}v(x)$$

And recall that $T'(x) = -1/i(x)$, so

$$\frac{d}{dx}\left[e^{(r+\rho)T(x)}\hat{v}(x)\right] = \frac{e^{(r+\rho)T(x)}}{i(x)}v(x)$$

Integrating from x to $\bar{x}$ and using the fundamental theorem of calculus, we have

$$e^{(r+\rho)T(\bar{x})}\hat{v}(\bar{x}) - e^{(r+\rho)T(x)}\hat{v}(x) = \int_x^{\overline{x}} \frac{e^{(r+\rho)T(y)}}{i(y)}v(y)dy$$

where we have changed the running variable for integration on the RHS from x to y. Now, from the terminal condition

$$\begin{aligned} -e^{(r+\rho)T(x)}\hat{v}(x) &= \int_x^{\overline{x}} \frac{e^{(r+\rho)T(y)}}{i(y)}v(y)dy \\ \Rightarrow \hat{v}(x) &= -\int_x^{\overline{x}} \frac{e^{-(r+\rho)(T(x)-T(y))}}{i(y)}v(y)dy \end{aligned} \tag{31}$$

Step 3. Changes of Variables The key step in simplifying expression (31) is to move the right-hand side integral from stage space to time space. Let

$$\begin{aligned} \tau &= T(x) - T(y) \\ \Rightarrow d\tau &= \frac{dy}{i(y)} \end{aligned}$$

Note further that $y = x \Leftrightarrow \tau = 0$ and $y = \bar{x} \Leftrightarrow \tau = T(x)$, so changing the integration bounds, we find

$$\hat{v}(x) = -\int_0^{T(x)} e^{-(r+\rho)\tau} v(y(\tau)) d\tau \tag{32}$$

where $y(\tau)$ is defined as the position of the project that starts at x at $\tau = 0$ and evolves according to $dy = i(y)d\tau$.

Consider in turn the sequence formulation of the firm problem. Instead of summing cash flows over time, we can sum cash flows over the states that the project will go through until its eventual completion. Formally,

$$v(y) = -\int_y^{\bar{x}} \frac{e^{-r[T(y)-T(u)]}}{i(u)} \left[i(u) + \kappa\left(i(u)\right) \right] du + e^{-rT(y)} pz \tag{33}$$

The left-hand side is the value of a project starting in stage y. After $T(y)$ periods, it will be completed and yield pz. At each stage u until it reaches completion, the firm spends $i(u) + \kappa(i(u))$. Converting the sum from a time summation to a summation over positions follows from the same change of variables considered above: each time step becomes $du/i(u)$, and we renormalize time to run from the time at which we are in stage y onwards. The bounds of the integral follow directly from the fact that the project starts at y and is finished once it reaches $\bar{x}$.

Substituting (33) into (32), we obtain

$$\begin{aligned} \hat{v}(x) &= -\int_x^{\bar{x}} \frac{e^{-(r+\rho)(T(x)-T(y))}}{i(y)} \left[-\int_y^{\bar{x}} \frac{e^{-r[T(y)-T(u)]}}{i(u)} \left[i(u) + \kappa\left(i(u)\right) \right] du + e^{-rT(y)} pz \right] dy \\ &= \underbrace{\int_x^{\bar{x}} \int_y^{\bar{x}} \frac{e^{-(r+\rho)(T(x)-T(y))}}{i(y)} \frac{e^{-r[T(y)-T(u)]}}{i(u)} \left[i(u) + \kappa\left(i(u)\right) \right] du dy}_{\hat{v}_1(x)} - \underbrace{\int_x^{\bar{x}} \frac{e^{-(r+\rho)(T(x)-T(y))}}{i(y)} e^{-rT(y)} pz dy}_{\hat{v}_2(x)} \end{aligned}$$

Step 4. Simplifying Algebra We start with $\hat{v}_1(x)$. We change the order of integration, so

$$\begin{aligned}
\hat{v}_1(x) &= \int_x^{\overline{x}} \int_y^{\bar{x}} \frac{e^{-(r+\rho)(T(x)-T(y))}}{i(y)} \frac{e^{-r[T(y)-T(u)]}}{i(u)} \left[i(u) + \kappa\left(i(u)\right)\right] du dy \\
&= \int_x^{\overline{x}} \int_x^{u} \frac{e^{-(r+\rho)(T(x)-T(y))}}{i(y)} \frac{e^{-r[T(y)-T(u)]}}{i(u)} \left[i(u) + \kappa\left(i(u)\right)\right] dy du \\
&= \int_x^{\overline{x}} \left[\frac{i(u) + \kappa\left(i(u)\right)}{i(u)}\right] e^{-(r+\rho)T(x)} e^{rT(u)} \left(\int_x^{u} \frac{e^{\rho T(y)}}{i(y)} dy\right) du
\end{aligned}$$

Noting that

$$\begin{aligned}
\int_x^{u} \frac{e^{\rho T(y)}}{i(y)} dy &= \int_x^{u} \left(\frac{d}{dy} - \frac{e^{\rho T(y)}}{\rho}\right) dy \\
&= -\frac{1}{\rho}\left(e^{\rho T(u)} - e^{\rho T(x)}\right)
\end{aligned}$$

We can write

$$\hat{v}_1(x) = \frac{1}{\rho} \int_x^{\overline{x}} \left[\frac{i(u) + \kappa\left(i(u)\right)}{i(u)}\right] e^{-r(T(x)-T(u))} \left(1 - e^{-\rho(T(x)-T(u))}\right) du$$

Last, change variables from u to $\tau = T(x) - T(u)$. Then, $du/i(u) = d\tau$, the bounds now run from 0 to $T(x)$, and we define u as the stage $y(\tau)$ of the project starting in stage x, i.e. for which $y(0) = x$. Putting all together,

$$\hat{v}_1(x) = \int_0^{T(x)} \left[\frac{i(y(\tau)) + \kappa\left(i(y(\tau))\right)}{i(u)}\right] e^{-r\tau} \left(\frac{1 - e^{-\rho\tau}}{\rho}\right) d\tau$$

Moving to $\hat{v}_2(x)$, we intergrate

$$\begin{aligned}\hat{v}_2(x) &= \int_x^{\overline{x}} \frac{e^{-(r+\rho)(T(x)-T(y))}}{i(y)} e^{-rT(y)} pz dy \\ &= pz e^{-(r+\rho)T(x)} \int_x^{\overline{x}} \frac{e^{\rho T(y)}}{i(y)} dy \\ &= e^{-rT(x)} pz \left(\frac{1 - e^{-\rho T(x)}}{\rho} \right)\end{aligned}$$

So bringing all together yields (13) and completes the proof.

H.5.2 Proof of Proposition 3

We omit z from the derivations to lighten notation. The results hold pointwise along the distribution of z. Differentiate the FOC

$$1 + \kappa'(\mathcal{I}(x,t,s)) = \frac{\partial}{\partial x} \mathcal{V}(x,t,s)$$

with respect to s to obtain

$$\kappa''(\mathcal{I}(x,t,s)) \frac{\partial}{\partial s} \mathcal{I}(x,t,s) = \frac{\partial}{\partial s} \frac{\partial}{\partial x} \mathcal{V}(x,t,s)$$

Switching the order of differentiation and evaluating at a steady state, we obtain

$$\kappa''(i(x)) \hat{i}(x,t) = \frac{\partial}{\partial x} \hat{v}(x,t)$$

where we defined $\hat{i}(x,t) \coloneqq \frac{\partial}{\partial s} \mathcal{I}(x,s,t) \Big|_{s=0}$. Once again, we conjecture $\hat{i}(x,t) = e^{-\rho t} \hat{i}(x)$ (and analogously for $\hat{v}(x,t)$), where as before $\hat{i}(x) \coloneqq \frac{\partial}{\partial s} \mathcal{I}(x,s,t) \Big|_{s,t=0}$. Thus,

$$\hat{i}(x) = \frac{\partial \hat{v}(x)/\partial x}{\kappa''(i(x))}$$

Differentiating (31) with respect to x using Leibniz's rule, we obtain

$$\begin{aligned}\frac{\partial \hat{v}(x)}{\partial x} &= \frac{1}{i(x)} \left[v(x) - (r+\rho) \int_x^{\overline{x}} \frac{e^{-(r+\rho)[T(x)-T(y)]}}{i(y)} v(y) dy \right] \\ &= \frac{1}{i(x)} \left[v(x) - (r+\rho) \hat{v}(x) \right]\end{aligned}$$

which completes the proof.

To get the capital budgeting rule, note that

$$\frac{\partial \hat{v}(x)}{\partial x} = \frac{v(x)}{(r+\rho)i(x)}\left[\frac{1}{r+\rho} - \frac{\hat{v}(x)}{v(x)}\right]$$

It remains to show that $\hat{v}_{perp}/v_{perp} = -1/(r+\rho)$. To see this, write down the HJB equation for valuing a perpetual bond with unit cashflow

$$ru(t) = 1 + \frac{\partial u(t)}{\partial t}$$

(or, more simply, the ODE describing of the value of a perpetuity over time). Given a first-order shock to discount rates, we can write

$$\left(r + se^{-\rho t}\right) u(s,t) = 1 + \frac{\partial u(s,t)}{\partial t}$$

Defining $\hat{u}(t) := \partial u(s,t)/\partial s\big|_{s=0}$, differentiate with respect to s

$$r\hat{u}(t) + e^{-\rho t}u(t) = \frac{d\hat{u}}{dt}(t)$$

And then conjecture $\hat{u}(t) = e^{-\rho t}\hat{u}$, where $\hat{u} := \partial u(s,t)/\partial s\big|_{s,t=0}$, so

$$\begin{aligned} re^{-\rho t}\hat{u} + e^{-\rho t}u &= -\rho e^{-\rho t}\hat{u} \\ \Rightarrow \frac{\hat{u}}{u} &= -\frac{1}{r+\rho} \end{aligned}$$

for u the $t = 0$ value of the perpetual bond. Relabeling appropriately yields the result.

H.5.3 Proof of Proposition 5

Let $\bar{\mathcal{Z}}(t,s)$ denote the entry threshold for a project. It must satisfy

$$\mathcal{V}(0, \bar{\mathcal{Z}}(t,s), t, s) = 0$$

where the restriction $x = 0$ comes from the project being nascent. From the implicit function theorem, it is immediate that

$$\frac{\partial \bar{\mathcal{Z}}(t,s)}{\partial s} = -\frac{\partial \mathcal{V}/\partial s}{\partial \mathcal{V}/\partial z}\bigg|_{(x,z)=(0,\bar{\mathcal{Z}}(t,s))} \tag{34}$$

We have already obtained the numerator, at least in steady state, when deriving the response of value to the shock. Towards the denominator, differentiate the time-dependent

HJB making use of the Envelope Theorem to obtain

$$r\frac{\partial \mathcal{V}}{\partial z}(x,z,s,t) = \mathcal{I}(x,z,s,t)\frac{\partial}{\partial x}\left(\frac{\partial \mathcal{V}}{\partial z}(x,z,s,t)\right)$$

$$\frac{\partial \mathcal{V}}{\partial z}(\bar{x},z,s,t) = p$$

and in the steady-state (i.e. $s = t = 0$), using lower-case letters to denote steady-state objects

$$r\frac{\partial v(x,z)}{\partial z} = i(x,z)\frac{\partial}{\partial x}\left(\frac{\partial v(x,z)}{\partial z}\right)$$

$$\left.\frac{\partial v(x,z)}{\partial z}\right|_{x=\bar{x}} = p$$

Once again, we have a first-order ODE in $\frac{\partial v(x,z)}{\partial z}$ with a given terminal condition. Here, recall that

$$\frac{\partial}{\partial x}e^{-rT(x,z)} = \frac{re^{rT(x,z)}}{i(x,z)}$$

so that

$$\frac{\partial v(x,z)}{\partial z} = pe^{-rT(x,z)} \tag{35}$$

satisfies the ODE and the terminal condition.

Returning to (34) and evaluating at a steady state, we have

$$\begin{aligned}\frac{\partial \bar{z}}{\partial s} &:= \left.\frac{\partial \bar{\mathcal{Z}}(t,s)}{\partial s}\right|_{s,t=0} \\ &= -\left.\frac{\partial v(x,z)/\partial x}{\partial v(x,z)/\partial z}\right|_{(x,z)=(0,\bar{z})} = -\frac{\hat{v}(0,\bar{z})}{\partial v(0,\bar{z})/\partial z} \\ &= -\frac{e^{rT(0,\bar{z})}}{p}\hat{v}(0,\bar{z})\end{aligned}$$

which is (16) after rearranging.

H.5.4 Proof of Proposition 6

We omit z from the derivations to lighten notation. The results hold pointwise along the distribution of z.

Fixed Capital Formation Fix any $z > \bar{z}$. After any shock, not necessarily first-order, the distribution evolves according to the time-dependent KFE. Integrating the KFE, we have

$$\frac{\partial}{\partial t}\int_0^{\bar{x}} g(x,t)dx = i(0,t)g(0,t) - i(\bar{x},t)g(\bar{x},t)$$

Now, integrate from $t = 0$ (the time the shock hits) to $t = \infty$, and so

$$\lim_{t\to\infty}\int_0^{\bar{x}} g(x,t)dx - \int_0^{\bar{x}} g(x,0)dx = \int_0^{\infty} \left[i(0,t)g(0,t) - i(\bar{x},t)g(\bar{x},t)\right] dt$$

where $g(x,0)$ is by definition the steady state distribution.

If the shock is temporary, the distribution reverts back to steady state, and so

$$\int_0^{\infty} \left[i(0,t)g(0,t) - i(\bar{x},t)g(\bar{x},t)\right] dt = 0$$

That is, the total outflow of projects must be equal to the total inflow of projects over time.

If the shock is small enough that z remains above $\bar{z}$ (or for any first order shock and $z > \bar{z}$), we have

$$\int_0^{\infty} \left[i(\bar{x},t)g(\bar{x},t) - f(z)\right] dt = 0$$

where we have used the initial boundary condition for the KFE for $z > \bar{z}$

$$i(0,t)g(0,t) = f(z)$$

But $f(z)$ is also the steady state outflow of firms, so this means that the area under the IRF of outflows (or capital formation if multiplied by z) is zero.

Accounting Investment The area "under" the curve is

$$\int_0^{\infty} \left[\int_0^{\bar{x}} i(x,t)g(x,t)dx - f(z)\bar{x}\right] dt$$

where $\int_0^{\bar{x}} i(x,t)g(x,t)dx$ is total accounting investment at time t and $f(z)\bar{x}$ is its steady state value. We want the area is zero.

Integrating the KFE, we have

$$\frac{\partial}{\partial t}\int_0^x g(y,t)dy = i(0,t)g(0,t) - i(x,t)g(x,t)$$

Now, integrate again from $x = 0$ to $\bar{x}$

$$\frac{\partial}{\partial t}\int_0^{\bar{x}}\int_0^x g(y,t)dydx = i(0,t)g(0,t)\bar{x} - \int_0^{\bar{x}} i(x,t)g(x,t)dx$$

Consider the left-hand side. Switching the order of integration, we have

$$\begin{aligned}\int_0^{\bar{x}}\int_0^x g(y,t)dydx &= \int_0^{\bar{x}}\int_y^{\bar{x}} g(y,t)dxdy \\ &= \int_0^{\bar{x}} (\bar{x}-y)g(y,t)dy\end{aligned}$$

And thus

$$\int_0^{\bar{x}} (\bar{x}-y)\frac{\partial}{\partial t}g(y,t)dy = i(0,t)g(0,t)\bar{x} - \int_0^{\bar{x}} i(x,t)g(x,t)dx$$

Integrating from $t = 0$ to $t \to \infty$, we obtain

$$\int_0^{\bar{x}} (\bar{x}-y)\left[\lim_{t\to\infty} g(y,t) - g(y,0)\right]dy = -\int_0^{\infty}\left[\int_0^{\bar{x}} i(x,t)g(x,t)dx - i(0,t)g(0,t)\bar{x}\right]dt$$

Last, if the shock is temporary and sufficiently small, we have $\lim_{t\to\infty} g(y,t) = g(y,0)$ and $i(0,t)g(0,t) = f(z)$, so

$$0 = \int_0^{\infty}\left[\int_0^{\bar{x}} i(x,t)g(x,t)dx - f(z)\bar{x}\right]dt$$

as desired.

H.6 Discount Rates

We mapped the empirical shock into an increase of firm's discount rates. This appendix elaborates on our modeling choice. First, it reviews theoretical and empirical contributions that

substantiate this modeling choice. Second, it sketches a brief microfoundation that would directly connect the provisioning shock to higher discount rates.

Firm discount rates reflect multiple considerations. The traditional corporate finance prescription is to set discount rates equal to the cost of capital, which reflects both equity and debt financing costs. Banks directly influence the latter via lending rates. Hence, turbulence in the banking sector would translate into more expensive debt financing and higher discount rates. Indeed, Hubbard et al (2002) provide early cross-sectional evidence in the US that poor bank health correlates with higher lending rates. Further, there is voluminous empirical evidence that banking distress or higher bank funding costs increases lending rates across multiple contexts. See Chava and Purnanandam (2011) for the US following the 1998 Russian crisis; Santos (2010) and Chodorow-Reich (2014) for the US following the collapse of Lehman Brothers and the GFC; Sette and Gobbi (2015) and di Patti and Sette (2016) for Europe; Abuka et al (2019) for a developing economy context; and Hale et al (2019) for cross-border evidence.

This literature also explores the mechanisms through which banking shocks pass through to lending rates. First, troubled banks face increases in funding costs. These higher marginal costs are passed into lending rates. If firms cannot substitute away from the troubled banks, their cost of debt rises. Even if firms can switch from affected to non-affected banks, many firms do not. In fact, part of this literature provides evidence that switching lenders is costly, especially in times of banking turbulence. One of the main explanations for these sticky firm-bank relationships is the prevalence of relational contracting and adverse selection in lending markets (Stiglitz and Weiss 1981, Sharpe 1990). Repeated transactions between a lender and a borrower allows the lender to acquire information about the borrower over time. Hence, lending rates become more favorable within the main relationship relative to other arms-length lenders. Switching lenders in times of banking distress throws a borrower into the general pool, which is offered higher rates due to adverse selection concerns. This mechanism has been empirically validated in multiple studies (Sette and Gobbi 2015, Bolton et al 2016, Banerjee et al 2021, Jimenez et al 2021).

Morais et al (2020) provides direct causal evidence that shocks that increase bank loan loss provisions pass through to lower borrowing, shorter maturity, and higher lending rates. They study the introduction of a expected provisioning requirements in Colombia in the mid-2000s. The reform made changes to provisioning requirements based on arbitrary firm-size thresholds, thereby bolstering identification claims; and was implemented during a period of economic stability and growth, similar to the macroeconomic context of India at the time of the AQR.

Following the regulatory change, Morais et al (2020) estimate that banks increased loan loss provisions on borrowers above the threshold size by 4% relative to borrowers below the threshold size. They also find a 50bps relative increase in average lending rates, a 10%

contraction in loan volumes, a 5% decline in average maturity. Importantly, these effects were quick to materialize – the cumulative effects are reached within one year of the reform's implementation. Further, these effects are sizable and comparable to the effects of large banking shocks estimated in the literature described above.

It is possible to microfound the pass-through from shocks to loan loss provisions into lending rates as follows.[59] Consider a setup with multiple banks and firms as in Herreño (2023), which delivers (i) a downward-sloping demand curve for credit and (ii) lending shares across banks for each firm. Lending is risky: a fraction of loans become nonperforming and may default. Banks set lending rates not only based on loan demand and default risk, but also on provisioning rules (Bouvatier and Lepetit 2012). The marginal loan increases required provisions and reduces bank earnings (Walter 1991), so optimal loan pricing consists of a risk-adjusted mark-up over funding costs (i.e. deposit rates or interbank market loans) plus the provisioning opportunity costs. Regulators can only imperfectly detect underprovisioning. Banks thus hide NPLs to reduce provisioning costs, offer more competitive lending rates, and gain market share. The India Asset Quality Review is a monitoring shock that forces banks to put up provisions, which then increases lending rates.

Discount rates could have reacted through channels other than lending rates. The bank shock can raise the value of cash inside the firm by reducing credit supply. The discount rate shock partly captures the higher value of cash, as more recent cash flows become more valuable relative to delayed cash flows when discount rates rise. Another modeling device used to capture this channel is firm-level borrowing constraints. We elaborate on our choice of discount rates versus borrowing constraints on Appendix H.7. Last, higher discount rates may reflect behavioral or organizational frictions. Managers may become more risk-averse in times of scarce credit; or CFOs might use the shock as a disciplining device for internal capital markets, forcing managers to adopt more stringent discount rates.

H.7 Spending Constraints

In the main text, we modeled the credit shock as an increase in the discount rate. An alternative approach maps the credit shock to a tightening of the firm's ability to borrow. In this appendix, we sketch such a model. We then argue in favor of the discount rate shock as the preferred channel to rationalize our empirical findings.

Consider a firm building $N > 1$ projects. The discreteness simplifies exposition and is without loss of generality. The building technology is the same as in the main text. There is now a spending constraint. If a firm has N projects, it can invest up to E_N across all projects.

[59] For the sake of brevity, we only describe the model setup and the main result. Derivations are lengthy, but available upon request.

To fix ideas, consider a firm with a single project ($N = 1$). Optimal investment $i \geq 0$ solves

$$\begin{aligned} rv(x) &= \max_i -[i + \kappa(i)] + iv'(x) \\ \text{s.t.} & i + \kappa(i) \leq E_1 \\ & v(\bar{x}) = p \end{aligned}$$

Unconstrained investment, as before, equates the marginal cost $1 + \kappa'(i^*(x))$ to the marginal value $v'(x)$. If investment is constrained, the firm sets

$$\bar{i}(x) + \kappa\left(\bar{i}(x)\right) = E_1$$

so that optimal investment is given by $i(x) = \max\left\{0, \min\left\{i^*(x), \bar{i}(x)\right\}\right\}$.

Suppose instead the firm was building two projects. Denote by x_n the stage of project $n = 1, 2$. The firm now solves

$$\begin{aligned} rV(x_1, x_2) = \max_{i_1, i_2} & -[i_1 + \kappa(i_1) + i_2 + \kappa(i_2)] + i_1 \frac{\partial V}{\partial x_1} + i_2 \frac{\partial V}{\partial x_1} \\ \text{s.t. } & i_1 + \kappa(i_1) + i_2 + \kappa(i_2) \leq E_2 \end{aligned}$$

Note that E_2 can be different from E_1. For example, once a project is finished, available capital inside the firm increases and could relax the spending constraint. That would be the case if (i) the windfall from project completion became cash that could be immediately spent; or if (ii) completion of the project relaxed borrowing constraints through a collateral-based or earnings-based channel. In such cases, $E_2 < E_1$. Alternatively, ex ante budget allocations could increase with the number of projects, making $E_2 > E_1$.

The terminal conditions for each project are

$$V(x_1, \bar{x}) = p + v(x_1)$$

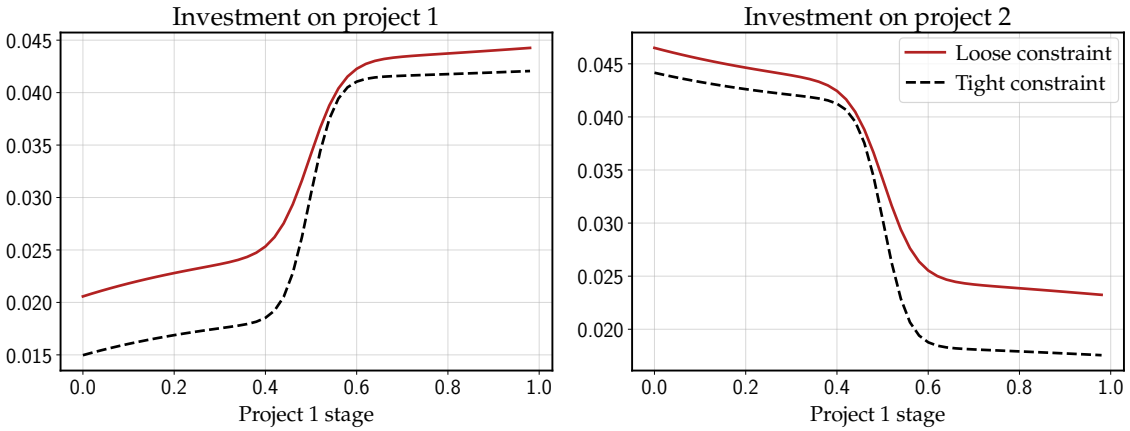
$$V(\bar{x}, x_2) = p + v(x_2)$$

The first condition states that the value of having project 2 completed is the return to project 2 plus the continuation value of still having project 1 under implementation. The second condition states the same when project 1 is completed first. For expositional simplicity, we assume equal returns across projects. The necessary conditions for optimal investment are now

$$1 + \kappa'(i_j) = \frac{1}{1 + \lambda_j} \frac{\partial V}{\partial x_j}$$

where λ_j is the Lagrange multiplier on the spending constraint. We index λ by j to make explicit the dependence on the total budget E_j. Optimal capital budgeting thus implies equal-

Figure A22: Optimal Investment with Spending Constraints



Notes: the figure plots the optimal investment rate on each project as a function of project 1's stage, fixing the stage of project 2 at 50%. Parameter values for the numerical example are $\bar{x}_1 = \bar{x}_2 = z_1 = z_2 = 1$, $E_2 =$ (tight financial constraint), $E_1 =$ (loose financial constraint), and $\kappa(i) = \kappa i^2/2$.

izing the ratio of marginal values to marginal costs across projects.

To illustrate the economics, we resort to a numerical example. We assume $E_1 > E_2$, so completing one project *relaxes* the spending constraint. We fix project 2 at 50% completion. We then ask how investment in each project varies as a function of project 1's stage under two scenarios: tight vs loose spending constraints. Appendix Figure A22 presents the results.

As in the model without spending constraints, investment in project 1 is an increasing function of its own stage, independent of the constraint. With the aggregate spending constraint, investment in project 2 becomes a decreasing function of project 1 when the constraint binds. The intuition is simple: the more advanced project 1 is, the higher is the marginal value of investing in project 1 relative to project 2. The firm prefers to prioritize the project that is closer to completion in order to receive the terminal cash flows. When financial constraints are tighter, the investment schedule shifts down across both projects, reflecting the shared factor $(1 + \lambda_j)$ increasing the marginal cost of investment.

Suppose we start from the loose scenario. A credit shock then lowers the spending limit, moving us to the tight scenario. For illustration, suppose this is a permanent, unanticipated shock. Aggregate investment must mechanically drop. In the cross-section, both projects cut investment. As such, the "average" project within the firm is scaled back. The investment cut for the average project is the empirical counterpart of our regression estimate in this model. As such, a model with spending constraints *cannot* rationalize the robustly positive hazard effects on the average investment project. What spending constraints *can* rationalize are the heterogeneous hazard effects across projects of different stages.

We refrained from writing down a firm simultaneously optimizing (i) its investment across multiple projects and (ii) its aggregate capital structure subject to (iii) occasionally

binding borrowing constraints. Such approach would require three features. First, we would need to keep track of the entire distribution of projects, as we currently do. Second, we would need to solve for policies under an aggregate, occasionally binding constraint on total investment.[60] Third, we would need to solve for the resulting transitional dynamics following a temporary shock to the constraint. Individually, each task is manageable. But the interaction of these three elements tremendously increases the model's computational complexity.[61]

Taking stock, we see four reasons why we prefer to map the credit disturbance to a discount rate shock. First, it illustrates that the empirical patterns we observe – and therefore the basic theory of endogenous time to build – could arise from a neoclassical benchmark and a more nuanced understanding of the time value of money. Our empirical and theoretical results are not predicated on the particular form that financing frictions might take (e.g. asset- vs earnings-based).

Second, and perhaps most pragmatically, we make a computationally tractable choice that allow us to carry out meaningful estimation and counterfactual exercises while taking full advantage of the rich underlying heterogeneity in the project-level data. Third, we have sketched how the passthrough of the credit shock to the firm's discount rate could be microfounded without appealing to borrowing constraints at the firm level – though that need not be the only channel through which credit shocks would increase firm's discount rates. Last, from a more epistemological viewpoint, we appeal to Occam's razor.

This is not to say that interactions between endogenous time to build and firm-level financing frictions are not important. We believe they are an exciting area for further work: capital budgeting often requires managers to screen across multiple projects precisely due to organizational constraints on divisional spending. Our work hopes to precisely ignite further progress in that direction.

I Endogenous Time to Build and Bond Pricing

The results in Section 4 capture a broad economic mechanism related to (changes in) the time value of money. We illustrate this point by returning to standard fixed income pricing.

[60] An easier, though economically questionable approach would be to specify borrowing constraints at the project level, as if such projects could be individually collateralized. Project finance, however, is still nascent in India. Most of the corporate loans are not secured against specific assets.

[61] Indeed, models with liquidity or borrowing frictions like Bolton, Chen and Yang (2019) study joint optimization of investment and capital structure, but abstract from time to build and do not model the dynamic evolution of an entire distribution of projects.

Setup Consider a bond paying coupons $c(t)$ and with face value F. All cash flows are discounted at a rate r. The remaining time to maturity is T. The value of the bond is

$$V = \int_0^T e^{-rt} c(t) dt + e^{-rT} F$$

Recall that when interest rate changes, the change in the bond price is given by the bond's duration

$$\frac{\partial V}{\partial r} = -\int_0^T t e^{-rt} c(t) dt - e^{-rT} F \cdot T = -\text{Dur}(V)$$

This formulation maps to Section 4 as follows. The coupons are just the investment flows required to complete the project. The face value, in turn, is the return to completing the project, given by pz in the notation of Section 4. The bond price (or, value) V is akin to the project value $v(x, z)$, in which case the maturity of the project is instead the remaining time to project completion $T(x, z)$. The duration expression parallels Proposition 2, so that the $\frac{\partial V}{\partial r}$ is akin to $\hat{v}(x, z)$. The key difference is that we optimally choose investment flows for projects in Section 4. In turn, bond investors don't choose the path of coupons accruing to bonds (when they are not the issuers, at least).

"Accelerating" Bond Cash Flows Consider the following experiment. Suppose we "accelerate" the cash flows of the bond. To be precise, we shift all cash flows backwards in time by Δ. The last coupon is $c(T)$, which is now received at $T - \Delta$. The face value is also received at $T - \Delta$. At date 0, the coupon is now $c(\Delta)$ rather than $c(0)$. That is, the bond holder forfeits all coupon payments in the time interval $[0, \Delta]$. The value of this (new) bond is

$$V(\Delta) = \int_0^{T-\Delta} e^{-rt} c(t + \Delta) dt + e^{-r(T-\Delta)} F$$

where $\Delta = 0$ corresponds to the original bond. Consider a marginal change in the time shift Δ. We have,

$$\frac{\partial V(\Delta)}{\partial \Delta} = \int_0^{T-\Delta} e^{-rt} \frac{\partial c(t + \Delta)}{\partial \Delta} dt - e^{-r(T-\Delta)} c(T) + r e^{-r(T-\Delta)} F \tag{36}$$

To build intuition about (36), consider first the last two terms. We have

$$e^{-r(T-\Delta)} \left(-c(T) + rF\right) = -\frac{\partial V(\Delta)}{\partial T}$$

so that the last two terms correspond to the case where we just exogenously reduce the maturity of the bond, but do not shift any of the other cash flows. In that case, we lose the terminal coupon $c(T)$, but we get the face value quicker, which we value at rF. We then

discount the cash flows to today to obtain the marginal change in the bond value. For most bonds, coupon payments are small relative to face values, so that $\partial V(\Delta)/\partial T$ is positive. That is, bond prices should rise if maturities exogenously fell.

The first term of (36) reflects the fact that we are shifting all cash flows over time, not just the terminal cash flows. The cash flow that would have been received in period $t+\Delta$ is now received at time t. Rather than being discounted by $e^{-r(t+\Delta)}$, it is now discounted by e^{-rt}. Consequently, the value of the bond must change to reflect this new path of discount rates.

Note that

$$\frac{\partial c(t+\Delta)}{\partial \Delta} = \frac{\partial c(t+\Delta)}{\partial t},$$

which follows from the fact that we are uniformly shifting cash flows over time. Using this result, we can integrate the first term in (36) by parts

$$\begin{aligned}\int_0^{T-\Delta} e^{-rt}\frac{\partial c(t+\Delta)}{\partial \Delta}dt &= \left[e^{-rt}c(t)\right]_0^{T-\Delta} - \left[\int_0^{T-\Delta} -re^{-rt}c(t+\Delta)dt\right] \\ &= e^{-r(T-\Delta)}c(T-\Delta) - c(\Delta) + r\int_0^{T-\Delta} e^{-rt}c(t+\Delta)dt\end{aligned}$$

Bringing all together and rearranging, we find

$$\frac{\partial V(\Delta)}{\partial \Delta} = -c(\Delta) + rV(\Delta) \tag{37}$$

Expression (37) is a key object. When we shift all cash flows by Δ, we lose the marginal coupon today. What we gain is the flow value from holding a new bond without that coupon, but with a shorter maturity and the original cash flows. In bond markets, we see securities with the same coupons, but with different residual maturities being traded at the same time. For example, we might observe two sovereign bonds with equal coupons, but one has T days remaining until maturity while the other has $T-\Delta$ days remaining. For a bond investor with fixed discount rate r, how much would the investor value swapping the former for the latter? Since one bond is just an intertemporal shift of the cash flows of the other, exactly as in our experiment, expression (37) provides the answer.

Suppose now that the bond investor could pay $\kappa(\Delta)$ today to accelerate cash flows by Δ.[62] We assume κ is differentiable and increasing. The necessary condition for an optimal choice of "acceleration" is

$$\kappa'(\Delta^*) = \frac{\partial V(\Delta^*)}{\partial \Delta} \tag{38}$$

We assume that an interior solution exists. A priori Δ^* could be positive or negative. An

[62]One way to think about κ is to model the supply side of a bond market where broker-dealers must be compensated for supplying identical bonds of differential maturities to investors that would like to do such swaps. They must manage such inventory and charge a fee depending on the maturity swap.

investor could prefer to shift cash flows further into the future if it was expecting a coupon in the next Δ^* that was really large relative to the remaining cash flows accruing to the bond. For most bonds, however, we think that coupons are small relative to face values. That is, for must bonds, we tend to think that the capital gains accruing from receiving a large payoff earlier outweighs the lost coupons. Formally, (37) is positive and therefore $\Delta^* > 0$.

A notable feature of (38) is that it carries the same economic content as (8), the FOC for the investment problem with endogenous time to build. Both equate the marginal cost of accelerating cash flows to the marginal benefits of doing so. While expression (8) is written in stage space, expression (38) is written in time space. However, we know that $dx = idt$, so that (8) can be rewritten in time space and yield a parallel expression to (38). In short, the underlying economics carries across the bond and the project settings.

Suppose now that discount rates change, as in our empirical exercise. The value of "accelerating" cash flows changes, resulting in a change in Δ^*. From (38), it follows that

$$\frac{\partial \Delta^*}{\partial r} = \frac{\frac{\partial^2 V(r,\Delta^*)}{\partial r \partial \Delta}}{\kappa''(\Delta^*) - \frac{\partial^2 V(r,\Delta^*)}{\partial \Delta^2}} \propto \frac{\partial^2 V(r,\Delta^*)}{\partial \Delta \partial r} \tag{39}$$

which again bears a striking resemblance to (14), the expression characterizing the impact effect of a discount rate shock on investment flows.[63] Assuming convexity of κ, bond (project) investors prefer to speed up cash (investment) flows if the increase in discount rate increases the marginal benefit of speeding up cash (investment) flows. This corresponds to the first equality in expression (39). By Fubini's theorem, an equivalent interpretation is that bond (project) investors speed up cash (investment) flows if doing so reduces the bond (project) duration. This is precisely the intuition we emphasized in the main text.

Differentiating (37) with respect to r yields

$$\frac{\partial V(r,\Delta)}{\partial r \partial \Delta} = \frac{\partial}{\partial r}\left(rV(r,\Delta)\right) = \underbrace{V(r,\Delta)}_{\text{Acceleration}(+)} \quad \underbrace{-r \cdot \text{Dur}(V(r,\Delta))}_{\text{Discounting}(-)} \tag{40}$$

Expression (40) spells out the economic forces determining whether cash flows are sped up or slowed down. A first effect, which we call "acceleration", is mechanical. Holding fixed the value of the asset, higher discount rates means investors value more earlier cash inflows. This effect is always positive. The second effect, which we call "discounting", comes from the

[63] The only difference is that instead of just having the second derivative of the acceleration cost in the denominator, we also have $\partial^2 V(r,\Delta^*)/\partial \Delta^2$. For a bond with constant coupons, it's easy to show that this second derivative is always positive for any bond of finite maturity. Since the denominator is the second-order condition for a maximum, we assume it holds for simplicity, anchoring on the results for constant coupon bonds. The reason why only the second derivative of the acceleration cost appears in our expressions for the full model follows from the fact that the value function is defined directly as a function of states only, and not of controls, while the value of the bond $V(r,\Delta)$ depends on both states and controls (very much like an arbitrary utility or profit function).

fact that as we change discount rates, we change the NPV of future cash flows and therefore revalue the asset. To first-order, the changes in asset value are summarized by its duration. The total effect adds both terms, and is given by the NPV of all cash flows weighted by $(1 - rt)$.

Expression (40) immediately implies that the effect of discount rate shocks vary across similar bonds with different residual maturities. For bonds (projects) close to maturity (completion), duration is small, implying that it is optimal to speed up cash (investment) flows, consistent with Corollary (4). In turn, for bonds (projects) with large residual maturity (time to build), duration is large, implying it might even be optimal to slow down the pace of coupons (investments).

The parallel between bond pricing and project development is admittedly not one-to-one. Two key differences exist. First, we optimally choose the "coupons" (investment flows) of the project and therefore its residual "maturity" (time to build). Second, the project requires a fixed amount of investment to be paid in order to reap the terminal payoff. In turn, the bond pays the face value at maturity regardless of the path of coupons beforehand. In that sense, an experiment where we shift all of the bonds' cash flows, but do not require the remaining coupons to "add up" in value to the value of the coupons before the shift is not a perfect parallel to the project investment case. But even without the additional complications of designing a variational path for coupons that preserved their sum, we obtained the same intuition for the decision to speed up cash flows. All in all, while the parallel between bond pricing and project development is not perfect, it illustrates how the key forces driving the responses in both cases relate to the time value of money, and how changes in the price of cash flows today versus tomorrow have differing implications for long-lived assets with differing residual maturities.