Place-Based Policies and the Geography of Corporate Investment *

Cameron LaPoint† Shogo Sakabe‡

Yale SOM Columbia

October 26, 2021

Latest version here

Abstract

Growing spatial inequality has led policymakers to enact tax breaks to attract corporate investment and jobs to economically peripheral regions. We demonstrate the importance of multi-plant firms' physical capital structure for the efficacy of place-based policies by studying a bonus depreciation scheme in Japan which altered the relative cost of capital across locations, offering high-tech manufacturers immediate cost deductions from their corporate income tax bill. Combining corporate balance sheets with a registry containing investment by plant location and asset type, we find the policy generated big gains in employment and investment in building construction and in machines at pre-existing production sites, with an implied fiscal cost per job created of $17,000. These responses are driven by more financially constrained firms and firms which rely on costly but long-lived capital inputs like industrial machines. The policy did not generate positive local spillovers to ineligible plants or spillovers through inter-regional trade networks. Plant-level hiring in ineligible areas outstripped that in eligible areas, suggesting firms reallocated funds from the write-offs within their internal network. How multi-plant firms react to spatially targeted tax incentives ultimately depends on their internal network and their composition of intermediate capital inputs used in production.

Keywords: place-based policies, spatial firms, bonus depreciation, physical capital structure, long-lived assets, financing constraints

JEL classifications: E22, G31, H25, R12, R38

*We thank Costas Arkolakis, Song Ma, Takashi Unayama, David Weinstein, and participants in the Yale International and Spatial Economics Lunch and UEA North American Meeting for detailed comments and helpful advice. We are grateful to the Research Institute of Economy, Trade and Industry (RIETI) for providing access to the manufacturing firm Census microdata. We thank staff at the Development Bank of Japan (DBJ) for answering our questions about the corporate balance sheet data. We also thank the Center on Japanese Economy and Business (CJEB) at Columbia Business School for supporting this project by providing dissertation fellowships to both authors. Additionally, Sakabe thanks the Nakajima Foundation for generous financial support. We thank Sung Mo Koo and Melissa G. Li for their help with transcribing the corporate disclosure data used in this project, and Mingjun Sun for providing extraordinary research assistance. This research was funded in part by the International Center for Finance at Yale SOM. An earlier version of this paper circulated as RIETI Discussion Paper, No. 21-E-059. First draft: July 12th, 2021.

†Yale School of Management. 165 Whitney Avenue, New Haven, CT 06511. Email: cameron.lapoint@yale.edu; Web: http://cameronlapoint.com

‡Department of Economics, Columbia University, 1022 International Affairs Building, 420 W 118th Street, New York, NY 10027. Email: s.sakabe@columbia.edu

1 Introduction

In the summer of 2018, Governor Scott Walker and President Donald Trump brokered a deal with Taiwanese electronics giant Foxconn which promised to bring 13,000 jobs and $10 billion in investment to small town Mount Pleasant, Wisconsin, in exchange for a total tax subsidy package of over $4 billion. By the end of 2019, Foxconn had employed 281 workers and fulfilled only 2.8% of their investment pledge by building an empty showcase facility.[1] How can policymakers offer targeted business incentives for relocation while avoiding corporate reversals like the Foxconn case? And how can such policies be designed to deliver long-lasting investment and increased opportunities for residents of economically struggling areas?

To explore the tradeoff between targeting and local capital retention inherent in place-based policies (PBPs), as illustrated by the Foxconn deal, we examine a bonus depreciation scheme in Japan which altered the relative cost of capital across locations. The Japanese government rolled out the Technopolis program between 1984 and 1989 to promote regional industry clusters outside the main metropolises, offering high-tech manufacturing firms immediate cost deductions from their corporate income tax bill. These write-offs were granted as bonus depreciation, which allows firms to deduct an additional fraction of physical capital costs in the first year of an asset's tax life, including deductions for purchases of buildings used towards business operations. A follow-up policy enacted between 1989 and 1994, dubbed Intelligent Location, expanded the set of eligible areas and offered bonus depreciation to firms in certain upstream, non-tradable industries.

Using a series of staggered difference-in-differences (DD) specifications which define treatment at the firm level based on industry and plant locations, we find Technopolis was successful at generating investment in treated areas. The historical nature of the Japanese policy experiments and long time coverage of our data allow us to examine the long-run impact of local business tax incentives on regional economic development. In particular, we rule out "toe dipping," or firms making small reversible investments to capture tax benefits and then exiting shortly thereafter. For listed firms, capital and employment shares within a firm's internal network are stable three decades after the bonus depreciation incentives expired. Corporate investment responses were concentrated in construction projects on existing sites within the firm's network; we find granting firms Technopolis eligibility generated a 0.29 standard deviation increase in outlays for construction, and a 0.40 standard deviation increase in non-real estate assets.

Firms also increase their workforce by 5-7% (or, a 0.13-0.18 s.d. effect) within 10 years of implementation of a local bonus depreciation regime. Given that Technopolis primarily subsidized investment in industrial machinery, this suggests complementarity between high-tech capital and labor, contrary to recent concerns that machines may be displacing workers in certain sectors (Acemoglu & Restrepo 2020). Applying a partial equilibrium accounting approach which combines

[1] The Verge, "Inside Foxconn's Empty Buildings, Empty Factories, and Empty Promises in Wisconsin," October 19, 2020. Accessed on May 28, 2021.

the observed stream of claimed tax write-offs with our DD estimates of the employment response, we compute a fiscal cost from lost corporate income tax revenue of between $12,000 and $17,000 per corporate job created. This estimate is comparable to the $20,000 per job estimate of Garrett, Ohrn, & Suárez Serrato (2020) for bonus claims offered in the U.S. between 2002 and 2012. Overall, we conclude Technopolis was highly cost-effective on the labor market dimension relative to similar manufacturing subsidies and bonus depreciation schemes enacted elsewhere.

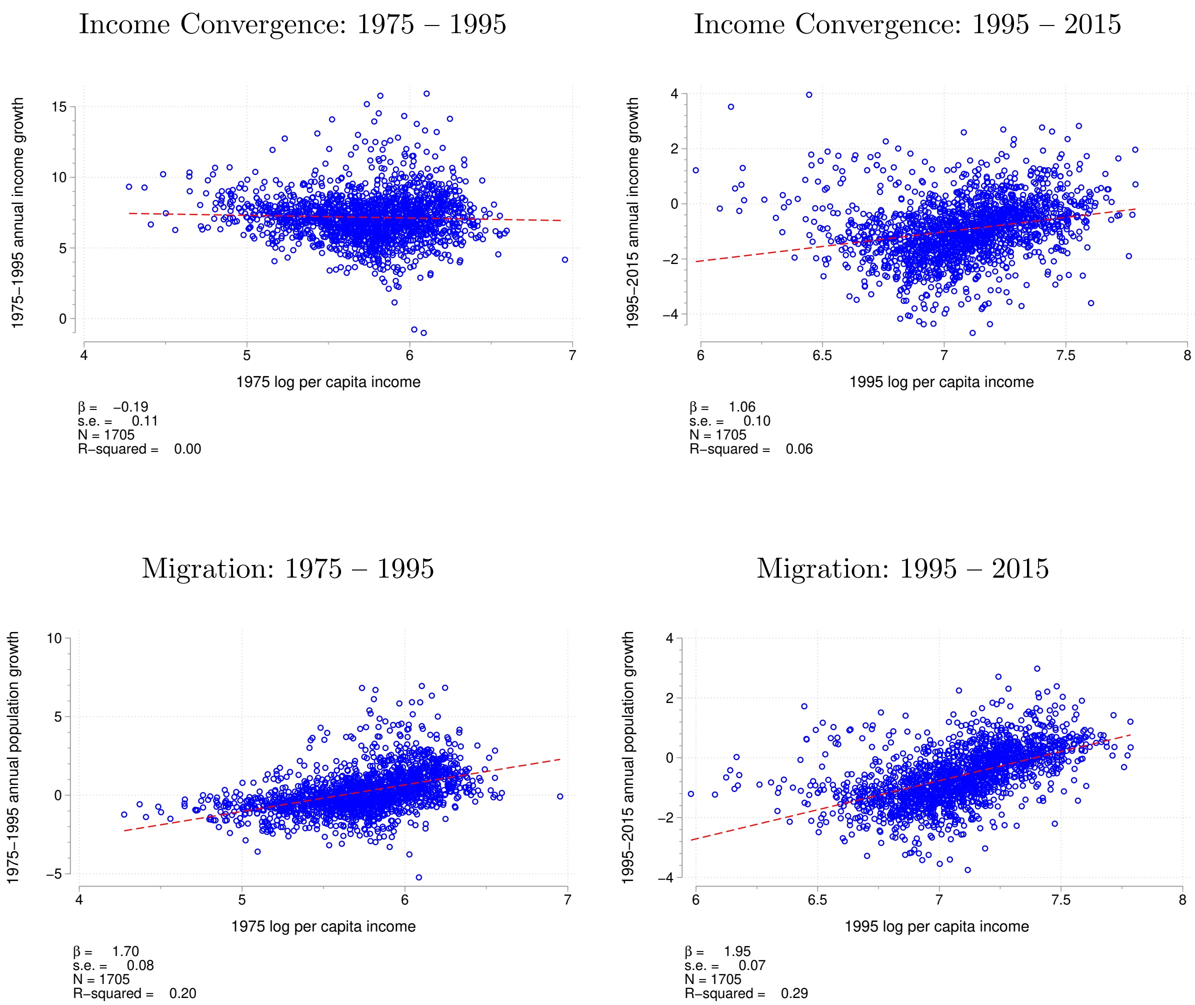
To highlight the crucial role of the physical capital structure in the effectiveness of spatially targeted tax incentives, we link a database containing balance sheets for all publicly listed Japanese firms with a registry containing corporate investment by plant location and asset type. Key to our research design is our ability to separate physical capital investment into six categories: construction projects, machines, tools, vehicles, buildings, and land. This allows us to identify firms, rather than coarse sectors, relying more on long-lived capital (buildings and machines) vs. short-lived capital (tools and vehicles). Long-lived capital firms gain more in an immediate cash flow sense from becoming eligible to claim spatial bonus depreciation, since normally the tax code would require them to amortize costs over a much longer period.

Another major advantage to merging corporate balance sheets with plant-level data is that we can move beyond intent-to-treat estimates towards average treatment effects by showing that firms actually make use of the tax incentives offered by the policy. Technopolis-eligible firms are 9 p.p. more likely to make bonus depreciation claims in the post-reform period (0.18 s.d. effect on the dollar value of claims). The observed effect on cash flows peaks after five years, which corresponds to the first kink point in the depreciation schedule, implying firms promptly act to maximize their deductions. Our results are robust to choosing among non-OLS estimators designed to account for the "negative weight problem" in aggregating heterogeneous treatment effects (Goodman-Bacon 2021) and for anticipation effects (Borusyak, Jaravel, & Spiess 2021) in staggered DD contexts.

Determining the efficacy of PBPs is of central importance given the widely documented growth in spatial inequality coinciding with the decline of traditional manufacturing since the 1970s. In the last three decades the U.S. has witnessed a stark decline in per capita income convergence (Ganong & Shoag 2017) and prime-age male employment rates (Austin, Glaeser, & Summers 2018), but a convergence in poverty rates across locations (Gaubert et al. 2021). Figure 1 shows that Japan has experienced an increase in directed migration and income *divergence* over the last few decades, as population aging has exacerbated the depopulation of the countryside and economic activity becomes increasingly concentrated around Tokyo.

Place-based policies are a catch-all term referring to transfers made conditional on economic activity in a location, but such policies can take many forms. The vast majority of research on PBPs has covered state and local tax subsidies and restricted attention to short-run effects due to data limitations (Bartik 2020). An exception is Kline & Moretti (2014), who study the Tennessee Valley Authority (TVA) over a century and conclude the TVA boosted national manufacturing productivity but employment gains were reversed when subsidies ended. De Simone et al. (2019)

FIGURE 1. Income Divergence across Japanese Municipalities



Notes: The figure shows how Japan has transitioned from weak income convergence to strong income divergence (top panel) and experienced an increase in directed migration (bottom panel) over the last 40 years. Population statistics from the quinquennial Census. Income data from the Cabinet Office. We impose modern municipality boundaries using the historical city code crosswalk available through RIETI (Kondo 2019), and exclude the 9 municipalities which merged with another municipality during the last available Census year of 2015.

compile a database of firm-specific U.S. local tax subsidies and contend the most successful subsidies are granted in jurisdictions where the initiatives receive little press coverage. Devereux, Griffith, & Simpson (2007) document that relocation grants in the U.K. were only effective at attracting plants when the new location already had plants of the same industry, suggesting the industry targeting of PBPs like Technopolis and Intelligent Location is crucial to their success. Criscuolo et al. (2019) study the same setting in the U.K. and find large effects on manufacturing employment for small firms, but larger firms "game the system" by accepting subsidies without increasing local activity.[2]

Much of the latest empirical literature on PBPs analyzes the Opportunity Zone (OZ) program introduced by the 2017 U.S. Tax Cuts and Jobs Act (TCJA) to foster local job growth. The program allows state governors to designate low-income Census tracts as OZs, subject to Treasury Department approval. Investors can defer capital gains taxes on investment in OZs for at least five years, or eliminate their tax liability entirely if they hold the assets for at least 10 years. Freedman, Khanna, & Neumark (2021) conclude these tax incentives had no statistically significant impact on resident employment, earnings, or poverty rates. Similarly, Chen, Glaeser, & Wessel (2019) document minimal capitalization into single family home prices, suggesting that homebuyers do not expect neighborhood change resulting from the OZ program in the near term. Arefeva et al. (2021) instead find designated OZ Census tracts experienced increased employment growth of 2-4 p.p. between 2017 and 2019.

In recent work, Kennedy & Wheeler (2021) note using investors' tax returns that the gains from OZs are highly unequal, with relatively well-off and gentrifying Census tracts receiving the bulk of investment under the OZ program. This raises the question of what are the distributional consequences of PBPs? We approach this question from three angles. First, motivated by evidence of spillovers from a manufacturing investment subsidy program in Germany (Siegloch, Wehrhöfer, & Etzel 2021), we look at spillovers to a control group of firms located in eligible Technopolis sites who are ineligible to claim bonus depreciation. We find no evidence of positive spillovers, but some evidence of crowd-out of non-real estate investment. Second, we show that indirect exposure to the policy through inter-regional trade networks had no effect on employment or investment beyond direct eligibility. Third, we match our sample of listed firms to their establishments and show that firms' hiring and intensive margin investment were concentrated in Technopolis *ineligible* areas. Thus, while we do not find evidence of toe-dipping, it appears firms used the tax write-offs to redirect some cash flow benefits towards areas not targeted by policymakers.

Two main features distinguish our policy setting from related local business incentive schemes in the U.S. First, our results point to the importance of providing *immediate* rather than deferred financial incentives for inducing firms to make irreversible investments in peripheral regions. Bonus depreciation offers firms an opportunity to transfer cash flows from far future deduction claims to the present, operating much like the capital gains tax deferral incentives of OZs. Second, the Technopolis

[2]Other prominent examples of PBPs include State Enterprise Zones (Neumark & Kolko 2010) which offer state-specific income, property, and sales tax benefits, and Federal Empowerment Zones which distribute employment subsidies and block grants to firms (Glaeser & Gottlieb 2008; Busso, Gregory, & Kline 2013).

and Intelligent Location policies we study are set at the national level, which limits the role of local political economy concerns (Slattery & Zidar 2020), or tax competition between jurisdictions (Mast 2020), in determining selection of treated regions and industries. In our case, eligible locations are selected for their manufacturing capacity and proximity to research universities, with incentives funded through national rather than local tax coffers.

Research on the economic impacts of PBPs has overwhelmingly examined wages and employment outcomes. In this paper we focus on how tax incentives can shift the spatial distribution of physical asset expenditures either by lowering the cost of capital at specific locations, or by mitigating frictions in capital markets. Such frictions might include financial constraints, as emphasized in a large corporate finance literature (e.g. Giroud & Mueller 2015, 2019), investment adjustment costs or "time to build" (Cooper & Haltiwanger 2006), and the costs of transporting tangible assets between locations (Ma, Murfin, & Pratt 2021). In a closely related paper, Zwick & Mahon (2017) demonstrate sectors using longer-lived assets like heavy industrial equipment exhibit larger investment responses to the 2001 and 2008 U.S. bonus depreciation reforms, which is consistent with models featuring fixed adjustment costs or financing constraints.[3]

When we rank firms based on measures of external financing constraints popular in the empirical corporate finance literature (e.g. Hadlock & Pierce 2010), we find that constrained firms completely drive the take-up of bonus claims, investment, and hiring. We recover firms' capital input shares using the methods of Hayashi & Inoue (1991) to rank firms based on their reliance on long-lived vs. short-lived assets. Assuming a constant returns to scale production function, buildings account for 47% of the capital input share for the average listed firm in our sample. This is particularly important because in the absence of bonus depreciation, commercial use buildings have a depreciation life as long as 65 years, implying a tax deduction *per annum* of only 1.54% of the acquisition cost under straight-line depreciation.[4] The outsize share of properties in firm production, combined with the maximum bonus depreciation claim of 15% for buildings under the two PBPs, renders relocation and outright ownership of new plants (or expansions of existing plants) in the treated regions substantially more attractive. Bonus depreciation is thus an especially potent force towards fostering irreversible investment.

Finally, our paper lends empirical support to mechanisms introduced in a growing macro-trade literature modeling the location decision of firms on the extensive margin (i.e. where to set up shop) and the intensive margin – that is, how many resources to allocate to a particular location.

[3]There is a voluminous empirical literature analyzing the investment response to corporate tax breaks. With the exception of Ohrn (2019), who studies state adoption of federal bonus depreciation policies, this literature has largely ignored the spatial dimension of investment responses. Other notable examples include Goolsbee (1998) and Chirinko, Fazzari, & Meyer (1999) on investment tax credits; Desai & Goolsbee (2004) and Yagan (2015) on the 2003 U.S. dividend tax cut; House & Shapiro (2008), Edgerton (2010) on bonus depreciation. In contrast to Zwick & Mahon (2017), Maffini, Xing, Devereux (2019) argue that the investment effect of accelerated depreciation allowances arises from changes to the cost of capital, rather than through alleviating firms' financial constraints.

[4]Long depreciation lives for buildings are not unique to Japan. Income-generating properties in the U.S. have a depreciation life of 39 years, while owner-occupied housing has a depreciation life of 27.5 years, implying annual straight-line deductions of 2.56% and 3.64% of acquisition cost, respectively.

Gaubert (2018) builds a model with agglomeration in which firms sort across cities on the extensive margin and argues PBPs like Technopolis and Intelligent Location which subsidize smaller cities have negative aggregate effects. In Fajgelbaum et al. (2018) firms sort into states which offer lower corporate income tax rates, and tax competition between states diminishes aggregate welfare. Like Jia (2008) and Holmes (2005, 2011), Oberfield et al. (2020) allow for sorting on both margins; their framework adds cannibalization and span of control and transport costs, but does not allow the physical size of plants to vary across locations. Importantly, none of these models directly includes capital in production, even though Dougal, Parsons, & Titman (2015) document agglomeration forces operating through capital rather than labor inputs.[5] Giroud et al. (2021) introduce a form of intangible capital, or local "knowledge" accumulation, to rationalize global productivity spillovers through multi-plant firms. As emphasized in LaPoint (2021), incorporating physical capital and financing constraints into a spatial sorting model can generate huge output responses to policy changes. We view our work as a critical first step towards putting physical capital back into models of spatial firms to assess the aggregate effects of place-based policies.

The paper proceeds as follows. Section 2 offers background on the Technopolis and Intelligent Location policies. Section 3 describes the plant-level Census data and corporate balance sheet data. Section 4 discusses our staggered difference-in-differences empirical strategy. Section 5 summarizes our findings on firm investment, hiring, and location choices in response to the place-based policies. Section 6 presents fiscal cost per job calculations. Section 7 concludes.

2 Policy Background

We study two place-based policies in 1980s and early 1990s Japan, dubbed the Technopolis policy and the Intelligent Location policy, respectively. Between 1984 and 1989, the Japanese government implemented the staggered rollout of the Technopolis policy targeting the manufacturing sector. The Intelligent Location program was implemented between 1989 and 1994 and targeted services firms that provided support for manufacturing, such as equipment leasing, machine repairing, software, and information and communications.

For both policies, we obtain the schedule of bonus depreciation rates from Ministry of International Trade and Industry (1995), which describes eligible asset classes and facilities at the 4-digit Japan Standard Industry Classification (JSIC) level. We collect the list of treated jurisdictions from the Japan Location Center (1999) history of the two policies. We provide in

[5] Other papers in the theoretical spatial firms literature include Ziv (2019), who examines city density, and like Gaubert (2018), studies an environment with firm sorting on the extensive margin. Kerr & Kominers (2015) study the rise of industry clusters like Silicon Valley in a model where agglomeration forces decay with distance due to interaction costs. Walsh (2019) allows for extensive margin firm sorting to show how new firm entry amplifies local shocks by attracting high-wage workers. In some models, (e.g. Forslid & Okubo 2014) firms paying a fixed cost to enter a market is synonymous with purchasing a building, but capital investment dynamics are not specified. While the spatial dimension is not explicitly modeled, Stein (1997) illustrates how headquarters allocate firm resources across projects subject to span of control costs.

Appendix A a full list of eligible JSIC industries and sites for Technopolis, and a full list of eligible industries and sites for Intelligent Location in Appendix B.[6] We now summarize the tax incentives and eligibility criteria for each program.

2.1 The Technopolis Policy

The Japanese government conceived of the Technopolis policy in 1983 as a way to jump-start industrial clusters in areas of the country geographically removed from the major metropolises of Tokyo, Osaka, and Nagoya. Another goal of the program was to diversify the economy away from heavy industries towards high-tech industries following the oil price shocks of the 1970s. To this end, the government chose sites satisfying three conditions: (i) possessing an already developed manufacturing sector, (ii) being in the vicinity of a major research university with a strong engineering department, and (iii) including a regional hub with a population of 200,000-300,000 residents (Ito 1995; Okubo & Tomiura 2012).

Panel A of Figure 2 maps by implementation year which municipalities were eligible sites for bonus depreciation claims under the Technopolis policy. While the law specified 26 Technopolis clusters, the official designation was conducted at the city code level.[7] In practice this meant that while each cluster contained a large regional city after which the cluster was named, there were as many as dozens of smaller towns and cities included in the cluster. For instance, the Hamamatsu Technopolis created in 1984 included the main city of Hamamatsu, the two small satellite cities of Tenryu, Hamakita, and two neighboring townships. In total, 141 municipalities were included in Technopolis sites: 62 became eligible in 1984, 27 in 1985, 11 in 1986, 19 in 1987, 17 in 1988, and 5 in 1989 as part of the Sapporo Technopolis.

Rather than featuring direct subsidies to either firms or local governments, Technopolis locations offered businesses a bonus depreciation schedule, where the bonus percentage declined beginning five years after the initial eligibility date specific to that location. Table 1 lists the rate schedule in percentages of asset acquisition cost for real estate and non-real estate assets. Buildings were eligible for half of the bonus depreciation percentage for which non-building depreciable assets were eligible. However, due to the long depreciation life for commercial buildings – ranging from 23 years for cold storage warehouses to 65 years for concrete office buildings – the bonus incentives for building purchases provided firms with substantial immediate cash flow benefits.

For instance, consider a firm purchasing a new concrete office building for \$1 million plus \$1 million in computers in 1990. If these investments were located in a Technopolis founded in

[6] We use the 1995 catalogue of bonus depreciation from MITI rather than earlier years because 1995 was the first year after the rollout of the last Intelligent Location sites (see the map in Panel B of Figure 2). Between 1993 and 1994, the government added a new kink point to the bonus depreciation schedule in each policy, which extended the period of eligibility to firms investing in catchment areas. No further changes were made to either policy after 1994.

[7] Each area in Japan is classified as a city (*shi*), town (*machi*) or village (*mura*), and receives an official Census city code. Throughout the paper, we account for municipal mergers by imposing modern boundaries to define geographic areas according to the 2015 list of city codes, and we refer to a city code as a "municipality."

TABLE 1. Technopolis Bonus Depreciation Incentives

Time from start date	Non-RE Bonus Rate	RE Bonus Rate
Within 5 years	30%	15%
Between 5 and 7 years	25%	13%
Between 7 and 8 years	20%	10%
Between 8 and 10 years	15%	8%
Between 10 and 12 years	14%	7%
$>$ 12 years	0%	0%

Notes: The table gives the bonus depreciation schedule by investment timing relative to the policy implementation date. The implementation date varies by Technopolis area. Non-RE Bonus Rate refers to the bonus depreciation as a percentage of acquisition cost for physical assets excluding buildings (e.g. tools and machinery), while RE Bonus Rate refers to bonus depreciation as a percentage of acquisition cost for buildings. The kink point between 10 and 12 years was added in 1994. Source: Ministry of International Trade and Industry (1995).

1985, the maximum rate of 30% on the computers ($300,000) and 15% on the building purchase ($150,000) could be deducted from corporate income tax liability. Assuming the firm faces a marginal tax rate of 40% – the statutory corporate income tax rate paid by firms in our data in 1990 – this implies an immediate cash flow of $180,000 arising purely from bonus claims. In 1990, without bonus depreciation, 25% of the computers (4-year depreciation life) and only 1.54% of the building cost (65-year depreciable life) could be deducted under linear depreciation, resulting in a much lower amount of $106,160 in immediate cash flow from tax savings. While the Technopolis bonus depreciation claims expired 12 years after implementation (e.g. by 2001 for the Technopolis designated in 1989), businesses could still claim the usual depreciation rates that applied to each asset class regardless of location. In Appendix C, we provide more detailed cash flow projections for the major cost amortization strategies available under the corporate income tax code.

The final dimension of Technopolis eligibility is the industry classification of the corporate tax unit.[8] We create a crosswalk to convert the historical Japan Standard Industry Classification codes (JSICs) valid under Technopolis to the modern classification system and report the full list of eligible industries in Appendix A. Of the 555 manufacturing industry codes, 66 JSICs (13%) are treated by Technopolis, including firms producing textiles, chemicals, pottery and ceramics, non-ferrous metals, machinery, precision tools, electronics, computers, and vehicles.

[8]Since bonus incentives apply towards corporate income taxes, the cash flow benefit accrues at the level of the tax unit, rather than at the level of an individual plant or a parent subsidiary.

TABLE 2. Intelligent Location Bonus Depreciation Incentives

Time from start date	Non-RE Bonus Rate	RE Bonus Rate
Within 2 years + Tokyo HQ	36%	18%
Within 3 years	30%	15%
Between 3 and 5 years	24%	12%
Between 5 and 7 years	20%	10%
> 7 years	0%	0%

Notes: The table gives the bonus depreciation schedule by investment timing relative to the policy effective date. The effective date varies by Intelligent Location area (see appendix for full list of start dates by area). Non-RE Bonus Rate refers to the bonus depreciation as a percentage of acquisition cost for physical assets excluding buildings, while RE Bonus Rate refers to bonus depreciation as a percentage of acquisition cost for buildings. Firms with a registered headquarters in the 23 central wards of Tokyo who relocate a portion of their operations to one of the treated areas qualify for a higher bonus percentage if they take advantage within 2 years of the policy date. The kink point between 5 and 7 years was added in 1994. Source: Ministry of International Trade and Industry (1995).

2.2 The Intelligent Location Policy

In 1988, the Japanese government passed a second regional policy program, called Intelligent Location (*zunō ritti*), which offered similar bonus depreciation incentives to firms in industries engaged in high-tech services such as software and telecommunications. The goal of this second policy wave was to build up the intermediate goods network in the clusters created by Technopolis, while also expanding the catchment areas for these clusters. Among the 26 Technopolis clusters, 15 regions were also designated Intelligent Locations. Figure 2 shows that the new Intelligent Locations were adjacent to the existing Technopolis sites. In total, 319 municipalities were included in Intelligent Locations, and of these, 244 were not previously eligible under Technopolis; 40 became eligible in 1989, 132 in 1990, 45 in 1991, 64 in 1992, and 38 in 1994.

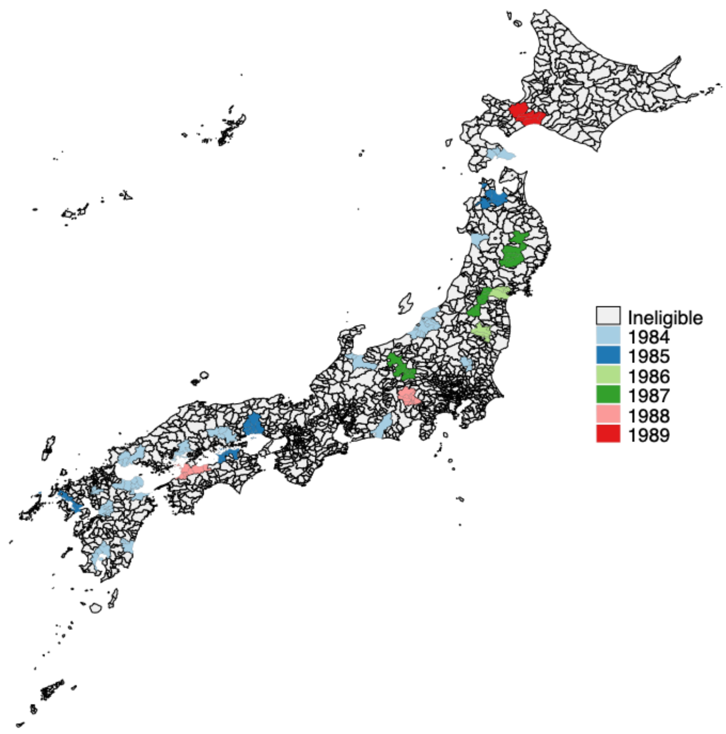
As Table 2 indicates, the bonus depreciation schedule under Intelligent Location shared many features with the Technopolis tax incentives. Buildings could be deducted at half the percentage of non-building investments, and the rates declined beginning three years after the local eligibility date, with complete phase out after seven years. One notable difference was the special treatment for firms headquartered in Central Tokyo; such firms could qualify for a 6 p.p. (3 p.p. for buildings) top-up from the maximum 30% bonus claim for investments made within two years.[9]

How economically distinct were the sites selected by the Technopolis and Intelligent Location policies? Table 3 compares local macroeconomic characteristics of policy sites to non-policy sites in 1980, prior to the implementation of Technopolis. Policy sites have more manufacturing employment and establishments, with a larger tangible capital stock than their ineligible counterparts. While

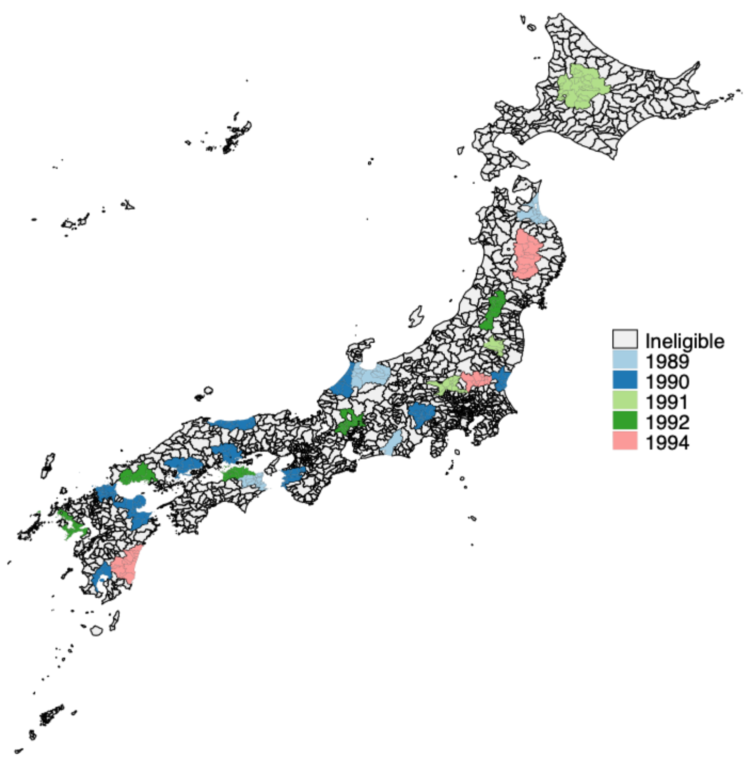
[9] While we do not observe the registered address for parent firms in our plant-level Census data, in future work we will explore whether listed firms headquartered in Tokyo – for which we do observe the registered address – were more likely to relocate resources under the Intelligent Location policy due to this surplus bonus rate.

FIGURE 2. Map of Areas Eligible for Bonus Depreciation

A. Technopolis Policy



B. Intelligent Location Policy



Notes: Panel A displays the map of Technopolis catchment areas color-coded by the year the policy applied to that area. Panel B does the same for areas selected for the Intelligent Location policy. Source: Ministry of International Trade and Industry (1995).

eligible areas are more populated on average than the universe of ineligible locations, they have similar per capita income and growth rates in plants and CRE prices. The main difference is in terms of property values. The average median price per square meter for commercial land is roughly one-third lower in eligible sites than in ineligible sites, and housing is also a slightly lower share of total household expenditures. Our empirical strategy differences out these *ex ante* discrepancies in the economic trajectory between eligible and ineligible sites by assigning treatment at the firm (or plant) level, which ultimately means comparing firms with otherwise similar balance sheets located in the same area but with different eligibility status due to the goods and services they produce.

3 Multi-plant Firm Data

This section describes the plant-level Census data and corporate balance sheet information we combine to assess the short-run and long-run effects of the two regional bonus depreciation schemes.

3.1 Census of Manufactures

Our main dataset consists of the plant-level microdata from the the Census of Manufactures (COM, or *kōgyō tōkei chōsa* in Japanese) conducted by Ministry of Economy, Trade and Industry (METI) for each year from 1980 to 2000. In years ending in 0,3,5, and 8 (e.g. 1980, 1983, 1985, 1988) our data include all plants in the manufacturing sector regardless of size. However, in other survey years, METI only maintains microdata files for plants with four full-time employees or more, which excludes sole proprietorships. To form a balanced panel, we restrict our sample to all plants with four or more employees for which we have continuous annual survey responses. The COM data are valuable for studying responses to the Technopolis and Intelligent Policy initiatives given the findings in the corporate finance literature that 1) immediate cash flows from bonus depreciation help offset the large fixed costs of purchasing key production inputs (Zwick & Mahon 2017), and 2) financing constraints are more prevalent for very small firms who tend to rely on pledging physical collateral to obtain bank loans (e.g. Berger & Udell 1995; Adelino, Schoar, & Severino 2015; Bahaj, Foulis, & Pinter 2020).

In terms of variable coverage, the COM survey asks plants to report a snapshot of their basic operations within the survey year, including full-time and part-time employment, the total wage bill, inventory, and cost of intermediate goods used in production. Key to our analysis are the variables pertaining to physical capital investment such as the book value of properties, plants, and equipment (PPE), which can be decomposed into three categories: machines, land, and buildings. It is standard in the corporate finance literature to define investment as the year-on-year change in net book value of PPE plus accounting depreciation. Unfortunately depreciation is not separately recorded for each major capital good category, while bonus depreciation incentives differ by the use and type of asset. To isolate investment in each type of tangible asset, we instead rely on amounts reported towards the acquisition of new buildings, machines, and non-machine goods.

TABLE 3. Economic Characteristics of Eligible vs. Ineligible Locations

	Technopolis				**Intelligent Location**			
	Eligible		*Ineligible*		*Eligible*		*Ineligible*	
	Mean (s.d.)	[min,max]	Mean (s.d.)	[min,max]	Mean (s.d.)	[min,max]	Mean (s.d.)	[min,max]
Total mfg. employment	9,524 (13,887)	[136, 109,649]	5,706 (23,648)	[0, 723,990]	6,466 (11,999)	[34, 109,649]	5,919 (24,873)	[0, 723,990]
Heavy industry employment share	0.175 (0.128)	[0.025, 0.516]	0.212 (0.150)	[0.013, 0.875]	0.178 (0.127)	[0.025, 0.516]	0.214 (0.152)	[0.013, 0.875]
Establishments w/> 4 employees	370 (576)	[10, 4,769]	241 (1,389)	[1, 47,196]	246 (445)	[3, 4,769]	252 (1,472)	[1, 47,196]
Mfg. plant capital stock	3,527 (7,190)	[0, 5,961]	1,620 (4,605)	[0, 7,570]	2,334 (6,571)	[0, 7,570]	1,650 (4,416)	[0, 5,687]
Per capita income	556 (104)	[292, 764]	553 (158)	[196, 1,446]	536 (115)	[229, 803]	557 (162)	[196, 1,446]
Census population	119,885 (186,727)	[4,824, 1,401,757]	64,110 (279,303)	[225, 8,351,856]	75,536 (159,918)	[1,360, 2,153,666]	67,122 (293,185)	[225, 8,351,856]
Population > 65 y.o.	11,439 (14,653)	[568, 87,440]	5,783 (22,151)	[27, 686,436]	7,339 (13,063)	[178, 167,476]	5,997 (23,213)	[27, 686,436]
Median price/m^2 for CRE	63.93 (35.83)	[6.60, 180.00]	100.91 (95.33)	[6.35, 571.00]	66.22 (41.65)	[6.60, 180.00]	103.16 (97.50)	[6.35, 571.00]
Housing expenditure share	0.091 (0.024)	[0.027, 0.141]	0.096 (0.036)	[0.028, 0.241]	0.084 (0.023)	[0.027, 0.141]	0.100 (0.037)	[0.028, 0.241]
$\%\Delta^{1980-83}$ mfg. employment	9.8 (20.7)	[−32.0, 136.6]	6.3 (20.8)	[−100, 219.1]	6.8 (19.2)	[−100, 136.6]	6.5 (21.2)	[−100, 219.1]
$\%\Delta^{1980-83}$ establishments	7.1 (12.0)	[−12.5, 72,7]	6.4 (18.6)	[−72.7, 200.0]	6.1 (13.8)	[−66.7, 87.5]	6.5 (19.0)	[−72.7, 200.0]
$\%\Delta^{1980-83}$ CRE price/m^2	57.7 (40.1)	[10.3, 203.0]	69.8 (64.1)	[−37.1, 722.5]	62.9 (46.0)	[−9.2, 276.1]	69.5 (64.7)	[−37.1, 722.5]
# of municipalities	141		1,568		319		1,390	

Notes: The table provides the mean, standard deviation, and min/max range for local economic conditions among eligible vs. ineligible municipalities under Technopolis and Intelligent Location. All variables recorded in levels are as of the pre-reform period in 1980, except for the housing expenditure share which is as of 1981. Heavy industry employment share is the share of manufacturing employment (mfg.) engaged in chemical, petroleum/coal, steel, vehicles, non-ferrous metals, and metal refining 2-digit JSIC industries. Mfg. plant capital stock is the total PPE summed across local manufacturing plants in 10 millions of JPY. Median price/m^2 for CRE refers to the median price per square meter (in 1,000s of JPY) for commercial real estate in the CBD of the city. The housing expenditure share is the share of housing costs (rent + mortgage payments + repairs) in total expenditures, computed from the Family Income and Expenditure Survey. Manufacturing statistics from the METI Census of Manufactures, population counts from the Census, and CRE prices obtained from collapsing the MLIT appraisal surveys for commercial and industrial use properties. To obtain per capita income (in 1,000s of JPY), we use the Cabinet Office local statistics for taxable income and divide by total 1980 Census population. To compute these statistics, we impose modern municipality boundaries using the historical city code crosswalk available through RIETI (Kondo 2019).

3.2 DBJ Corporate Balance Sheet Data

While the COM data are comprehensive in their coverage of plants throughout the size distribution, the Census survey does not ask plants or their parent firms to report on the liabilities side of the balance sheet, or to provide detailed information on taxes and depreciation claims by type of physical capital good. The latter information is needed to compute measures of the cash flow gains from bonus depreciation, conditional on making investments in treated areas. To assess the potential role of financing constraints in the reallocation of resources across locations within the firm, we use the non-consolidated firm-level balance sheet totals compiled by the Development Bank of Japan (DBJ). The DBJ data include all firms listed on the Tokyo Stock Exchange: 1,615 firms as of 1980. We use years 1975 to 2000 as the sample period in our firm-level analysis.

Accounting for firm fixed effects is particularly important in our setting, because firms may differ in their responses to the regional policies depending on whether they already operate a plant in or near a catchment area. Official firm panel id numbers in the COM survey are available starting in 1994, while plant panel id numbers are available starting in 1986.[10] Moreover, while the COM survey asks plant representatives to indicate whether the parent firm's HQ is physically proximate, precise HQ addresses are unavailable prior to 1994.

Although location information is not directly available in the DBJ database, we obtain a snapshot of corporate geography in the pre-reform period by merging in the hand-collected data on listed firms' locations constructed by LaPoint (2021). Registered and production HQ locations are reported by the firm on the cover page of their annual securities filings – equivalent to the Form 10-K in the U.S. (known as the *yuhō* in Japanese) – and firms are required to report the municipality of any operating locations, regardless of whether the property is owned or rented.[11] Firms also allocate employees and book values of owned buildings and land to each facility reported in this section of their filings, which allows us to compare some plant-level outcomes before and after the reform.[12]

We match COM plants to their parent DBJ firms for the years 1986 – 2000 based on a fuzzy merge on the Japanese name of the parent firm in 1997 (the first year for which the name string is

---

[10] In future work, to track plants over the course of the early 1980s when Technopolis was first activated, we plan to backfill the panel using the plant master database (*kōgyō tōkei* converter) prepared and disclosed by the Research Institute of Economy, Trade and Industry (RIETI). Similarly, we use the Firm Master database (*kigyō* master) prepared by METI and the "Basic Survey of Japanese Business Structure and Activity" to construct consistent firm panel ids. This is the approach used in Bernard & Okubo (2016).

[11] DBJ obtains the corporate balance sheet information from the annual *yuhō* filed with the Financial Services Agency (FSA), so the locations are from the same regulated source as the rest of the data we use for listed firms. The historical *yuhō* are on file at the Tokyo Stock Exchange (TSE), and we downloaded the PDFs for all firms listed on the TSE in 1980, for all available years, from the Pronexus eol Corporate Information Database.

[12] Throughout the paper, we impose modern municipality boundaries using the historical city code crosswalk available through RIETI (Kondo 2019). Crosswalking geographic boundaries is particularly important in the Japanese context due to a flurry of municipal mergers driven by declining population in the countryside which has reduced the number of local jurisdictions from 3,278 in 1980 to 1,741 as of 2015. Our main results are virtually unchanged when we instead impose historical 1980 municipal boundaries to assign treatment status.

available in COM). We make two sample restrictions to ensure that firms in the DBJ sample can be matched to the COM data:

1. First, we require firms to have non-missing total assets for at least five consecutive years over the period 1980-1987. In effect, this means firms in our sample must report business activities for at least one year prior to and after the enactment of the Technopolis policy in 1984.

2. Second, for many Japanese firms (roughly 50% in 1980) the fiscal year runs from April in year $t-1$ to March in year t. To account for the fact that the COM survey responses refer to beginning or end of the calendar year, we assign firm-fiscal year observations to the calendar year in which the majority of their business activities occur. Thus, we assign a firm with a fiscal year ending in March in calendar year t to values reported in COM for survey year $t-1$. To limit any measurement errors due to timing, we drop firm-year observations with filing dates in May, June, or July, and any firm-year observations which change their fiscal year start and end months during the sample period.[13]

After imposing these restrictions, but before matching DBJ to COM, we arrive at a sample of 1,508 firms. After merging to COM, we obtain 870 firms consisting of 2,765 plants in 1980 which satisfy all sampling restrictions and for which we can compute the bonus depreciation variables which are key to our analysis.[14] The relatively small match rate between DBJ and COM is due to the fact that COM only surveys firms engaged in manufacturing, while DBJ includes listed firms in all non-FIRE sectors of the economy.

Given the well-known skewness of firm-level outcomes, we winsorize all firm-level investment and employment outcomes using as thresholds the median plus/minus five times the interquartile range, as recommended by Chaney, Sraer, & Thesmar (2012). For variables which are close to mean zero, such as debt issuance, we winsorize at the 2nd/98th percentiles. In our preferred specifications for non-zero outcomes, we take the log of the outcome variable. We also estimate some specifications where we instead scale monetary outcomes by dividing by the firm's total book asset value in the year prior to the sample start date. The latter strategy accommodates cases where the variable can be negative (e.g. cash flow), while also addressing the econometric critique of Welch (2020) that scaling outcomes by lagged assets renders it difficult to disentangle the effect on the outcome of interest from the effect on the denominator.

Table 4 reports summary statistics using the full DBJ sample of 1,508 and the matched DBJ-COM sample of 870 manufacturing firms. Our full sample of listed firms looks very similar to the matched sample of manufacturing firms based on cash flows, employment, tangible asset composition, and investment (CAPX). The matched sample is slightly more likely to issue new debt or pay off existing debt during the sample time period, and has more physical assets as a fraction of the

[13] We check that our results are robust to subsetting to firms with a fiscal year end date in March.

[14] The matched DBJ-COM sample increases to 1,013 firms if we drop the requirement the first sample restriction that firms report non-missing total assets for five consecutive years.

balance sheet. Firms in the matched sample are 7 p.p. more likely to derive positive net income from bonus depreciation ($\mathbb{1}\{bonus > 0\}$). This makes sense given that the full DBJ sample includes non-manufacturing sector firms which were ineligible based on the Technopolis industry criteria. Beyond the fact that only manufacturing plants are included in the COM data, we do not worry about sample selection in moving from our overall full DBJ sample to the matched set of firms.

4 Empirical Strategy

Our empirical strategy is a staggered difference-in-differences (DD) which takes into account the spatial, industrial, and time-specific dimensions of eligibility for bonus depreciation under Technopolis. The main firm-level specification we estimate takes the form:

$$y_{j,k,t} = \gamma_j + \delta_t + \beta \cdot Treatment_{j,k,t} + \eta' \cdot \mathbf{X}_{j,k,t} + \varepsilon_{j,k,t} \tag{4.1}$$

where $y_{j,k,t}$ is an outcome, such as employment or investment in new construction, γ_j are firm fixed effects, δ_t are calendar year fixed effects, and $\mathbf{X}_{j,k,t}$ is a time-varying set of controls. $Treatment_{j,k,t}$ is a dummy equal to one if in calendar year t firm j operating in industry k is eligible to claim bonus depreciation under the Technopolis schedule in Table 1.

As described in Section 2, plants in 66 4-digit JSICs within the manufacturing sector across 141 municipalities were at some point eligible for these tax incentives, with implementation dates spanning 1984 to 1989. This means there are several possible ways to define the dummy $Treatment_{j,k,t}$. For our city-level analysis in Section 5.1 using data aggregated to the city $\times$ 2-digit manufacturing sector in COM, we assign eligibility at the city level, so $Treatment_{c,t} = Treated_c \times Post_{c,t}$, where $Treated_c$ is equal to one if city c is an eligible city, and $Post_{c,t}$ is equal to unity if year t is after the implementation date specific to that city.

At the firm level the definition of $Treatment_{j,k,t}$ is less obvious given the classic problem of pinning down the "location of the firm." For example, consider a firm which controls its HQ located in a Technopolis ineligible municipality, and two additional plants: one which is located in an eligible municipality where bonus depreciation on investment can be claimed starting in 1984, and another located in an eligible area where claims can be made starting in 1986. If we were to assign eligibility based on the location of the HQ (as is common in many corporate finance papers) we would conclude the firm is ineligible. Looking beyond the HQ, how do we break ties where multiple locations might imply several different treatment timings?

In the end, we resolve this issue by setting $Treatment_{j,k,t}$ equal to one if all three of the following sequential criteria are satisfied:

(i) **Firm j level.** Based on the facility locations reported in its 1980 *yuhō* the firm controls one

TABLE 4. Summary Statistics for Multi-plant Firms

	Full DBJ Sample				**Matched DBJ-COM Sample**			
	Mean	Median	10th pct.	90th pct.	Mean	Median	10th pct.	90th pct.
Construction in progress	0.02	0.01	0.00	0.11	0.03	0.01	0.00	0.11
Non-real estate assets	0.83	0.44	0.02	2.26	1.07	0.74	0.07	2.76
Real estate assets	0.64	0.33	0.07	1.91	0.72	0.47	0.11	1.74
PPE	1.61	0.93	0.17	4.18	1.90	1.37	0.28	4.31
CAPX	0.11	0.06	−0.02	0.57	0.09	0.06	−0.05	0.40
Employment	2,572	991	240	5,559	2,516	950	262	5,144
Long-term debt issues	0.01	0.00	−0.10	0.15	0.01	0.00	−0.14	0.19
Cash flow	0.03	0.01	−0.02	0.16	0.03	0.01	−0.04	0.16
EBITDA	0.22	0.13	0.02	0.57	0.24	0.16	0.00	0.64
OCF	0.31	0.18	0.03	1.15	0.30	0.20	0.03	0.82
Bonus depreciation	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01
$\mathbb{1}\{bonus > 0\}$	0.23	0.00	0.00	1.00	0.30	0.00	0.00	1.00
# of firm-years	38,374				13,688			
# of 1980 plants	3,470				2,765			
# of firms	1,508				870			

Notes: The left-hand side of the table provides summary statistics for the full sample of listed DBJ firms we use in our main firm-level analysis in Section 5, while the right-hand side provides statistics for the subset of DBJ firms which can be matched to manufacturing plants in the manufacturing Census. Yen-denominated variables are scaled by total book assets in the baseline year (1975). Variables are defined in a COMPUSTAT equivalent fashion. Real estate is the sum of the book value of buildings, land, and construction in progress, while non-real estate includes all other components of PPE, including machines, tools and precision instruments, and vehicles. CAPX is YOY change in the net book value of PPE plus accounting depreciation, scaled by total book assets at baseline. Long-term debt issues is defined as the YOY change in long-term loans payable, scaled by total book assets at baseline. Cash flow is net income less taxes paid. EBITDA is computed as operating income plus depreciation and amortization, and OCF is computed using the identity presented in Lian & Ma (2021). Bonus depreciation is net income from claiming bonus depreciation. $\mathbb{1}\{bonus > 0\}$ is a dummy equal to one in firm-years with strictly positive net income from bonus depreciation. We tabulate the total number of manufacturing plants firms list on their 1980 securities filings (i.e. the "Condition of Facilities" section of their *yuhō*).

plant located in an eligible Technopolis area.[15]

(ii) **Industry k level.** The parent firm operates in one of the eligible 4-digit JSIC industry codes. We crosswalk by hand the 4-digit DBJ industry codes to the 2008 JSIC classification system to determine eligibility under this criterion.

(iii) **Timing t.** If the firm fulfills the above two criteria, then we set $Treatment_{j,k,t}$ equal to unity in any year t equal to or greater than the minimum year of eligibility across all eligible plants in the firm's 1980 internal network.

Applying these criteria implies the decomposition of $Treatment_{j,k,t} = Treated_{j,k} \times Post_{j,t}$. In cases such as the above three-plant example where one plant is eligible in 1984 and another in 1986, we set $Post_{j,t} = 1$ if $t \geq 1984$, and $Treated_{j,k} = 1$ if the firm is in an eligible industry. In sum, our DD model in (4.1) is a staggered DD where several potential within-firm treatments are stacked up via $Post_{j,t}$.[16]

In the above empirical models, treatment is an absorbing state, so the $Post_{j,t}$ dummy implicit in $Treatment_{j,k,t}$ never turns off. The Technopolis policy lasted into the early 2000s given that the last catchment area was formed in 1989 and bonuses could be claimed up to 12 years after the implementation date for an eligible area. Due to the strong overlap between Intelligent Location and Technopolis, we argue that even the Technopolis areas formed earlier in the 1980s would have continued to be partially treated under Intelligent Location, even though the industry composition of treated firms may have differed between the 1980s and 1990s. Further, in Section 5.4, we rule out any direct effects of Intelligent Location on areas already treated by Technopolis, but use a multiple treatment version of regression (4.1) to provide evidence that the two policies may have amplified each other through local general equilibrium effects.

Identification of treatment effects in a staggered reform DD setting is challenging given that the composition of the treatment and control groups is changing over time, leading to potentially negative weights on average treatment effects (ATEs) for some group-time cells (Goodman-Bacon 2021). To fix ideas, suppose we estimate the following event study version of (4.1):

$$y_{j,k,t} = \gamma_j + \delta_t + \sum_{t=1, t\neq t_0}^{T} \beta_t \cdot Treatment_{j,k,t} + \eta' \cdot \mathbf{X}_{j,k,t} + \varepsilon_{j,k,t} \tag{4.2}$$

[15] We do not require the firm to own either the building or land to satisfy this criterion, but we do require them to report some strictly positive book value of physical assets at the location. However, given that CRE space in Technopolis areas is far less expensive than in ineligible areas (see Table 3), the vast majority of firms own some property attached to plants in Technopolis areas. 99% of DBJ firms own some building or land among all the facilities itemized in 1980.

[16] We acknowledge this is not the only way to sort firms into eligibility. For instance, in a frictionless world without transport costs, if firms simply purchase physical capital through a plant in an eligible area and then move the resources to their HQ site, then only the industry determines eligibility, and we can write $Treatment_{k,t}$. Ultimately this is an empirical question that gives rise to several placebo tests. Interestingly, we only find effects on firm-level employment, investment, and bonus claims once we impose all three criteria (i)–(iii).

where now the β_t allow for dynamic effects of Technopolis eligibility which are measured relative to period t_0. To interpret β as the average treatment effect on the treated (ATT), the parallel trends assumption for potential outcomes without treatment must hold, and there must be no anticipatory effects. To examine the validity of the parallel trends assumption, we apply the imputation estimator of Borusyak, Jaravel, & Spiess (2021) [hereafter, *BJS*], which is robust to treatment effect heterogeneity. Relative to other estimators designed to handle bias in staggered rollout scenarios, *BJS* has the advantage of allowing us to explicitly model anticipatory leads.

Since new Technopolis sites were announced within the year prior to the implementation date, we allow for anticipation effects of up to one year in our reported DD estimates. We accommodate anticipation effects by shifting forward $\beta_t \to \beta_{t+1}$ in event study specification (4.2).[17] In Appendix E, we assess the importance of anticipatory effects for our main results by comparing the *BJS* estimator to the estimators of de Chaisemartin & D'Haultfœuille (2020), which uses not-yet treated units as controls, and of Sun & Abraham (2021), which only uses never-treated units as a control group.[18] *BJS* uses a two-step approach, which includes never-treated and not-yet treated units in the first step, and then extrapolates the model to treated potential outcomes in the second step by imputing untreated potential outcomes.

Finally, our estimates are intent-to-treat (ITT) in the sense that the DD models yield the impact of Technopolis *eligibility* at the firm and/or plant level on investment and employment. The "first stage" effect of Technopolis eligibility on overall bonus depreciation claiming behavior is informative for scaling up this reduced form effect to an ATE. While we do not observe the precise provision in the tax code that allows firms to make their depreciation claims, it is difficult to imagine a scenario through which Technopolis lowers the cost of claiming bonuses available under rules from the pre-existing tax code. We demonstrate in the next section that bonus claiming substantially increases on the extensive margin (by around 9 p.p. in most specifications), which validates our proposed mechanism, and suggests we are identifying treatment effects of the policy.

5 Firm Employment & Investment Responses

In this section, we report our main results from estimating the staggered DD models described in Section 4. As an executive summary, we find in response to Technopolis eligibility firms become more likely to claim bonus depreciation, leading to higher cash flow which peaks several years after the reform. Firms also increase their employment, long-term debt issuance, and outlays towards construction projects and non-real estate assets. These effects are driven by *ex ante* financially constrained firms.

[17] As recommended by Borusyak, Jaravel, & Spiess (2021), we do not shift forward the β_t for anticipation effects when we test for parallel trends via separate regressions on untreated observations.

[18] We exclude the Callaway & Sant'Anna (2021) estimator from our robustness checks since it produces identical results to the Sun & Abraham (2021) estimator for the baseline versions of (4.1) and (4.2) without covariates.

5.1 City-level Evidence of Extensive Margin Responses

We begin by aggregating the Census of Manufactures to the city $\times$ 2-digit industry level and estimating versions of (4.1) at the city level, where $Treatment_{c,t} = Treatment_c \times Post_{c,t}$. Figure 3 plots the dynamic effects of $\widehat{\beta}_t$ on log city-level manufacturing employment (Panel A) and the log number manufacturing establishments (Panel B) from estimating equation (4.2). We allow for one-year anticipation of Technopolis eligibility and apply the *BJS* estimator for staggered DD designs. We obtain a balanced panel of 1,699 municipalities which continuously supply information on employment and establishments.[19]

The event study analysis reveals a clear, but slow-moving gap in the evolution of employment and plant creation between Technopolis eligible cities and ineligible cities. For employment, this gap widens starting four years after the introduction of tax incentives ($\widehat{\beta}_5$). Ten years after the reform, employment is 13% higher in eligible sites, while the number of establishments is 6% higher. The fact that Technopolis was associated with growth in new plants points to the success of the policy at generating long-lasting investment in the targeted regions.[20]

Given the summary statistics in Section 2, it is clear that locations selected for the Technopolis and Intelligent Location programs have a distinct local economic profile which is reflected in the strong pre-trend in the event study for employment. Technopolis was enacted in the background of one of the largest real estate booms in modern history, and eligible areas both started with lower commercial real estate (CRE) price levels and experienced more muted price growth during the 1980s. However, within-region, Technopolis sites were selected based on proximity to major research universities, which means they were more economically dynamic than neighboring cities. We attempt to control for trends related to the real estate boom by computing median price per square meter for CRE as of 1980. We find qualitatively similar effects on employment and extensive margin investment when we do so, but the standard errors blow up because our sample drops down to only 375 cities for which we have CRE appraisal data.[21] The ability to more precisely measure eligibility at the 4-digit industry $\times$ location level and difference out some of these local macro trends motivates our firm-level analysis in the next subsection.

5.2 Firm-level Analysis

In this subsection we present our main analysis which explores the effects of Technopolis eligibility at the firm level on cash flow, hiring, investment, and debt issuance.

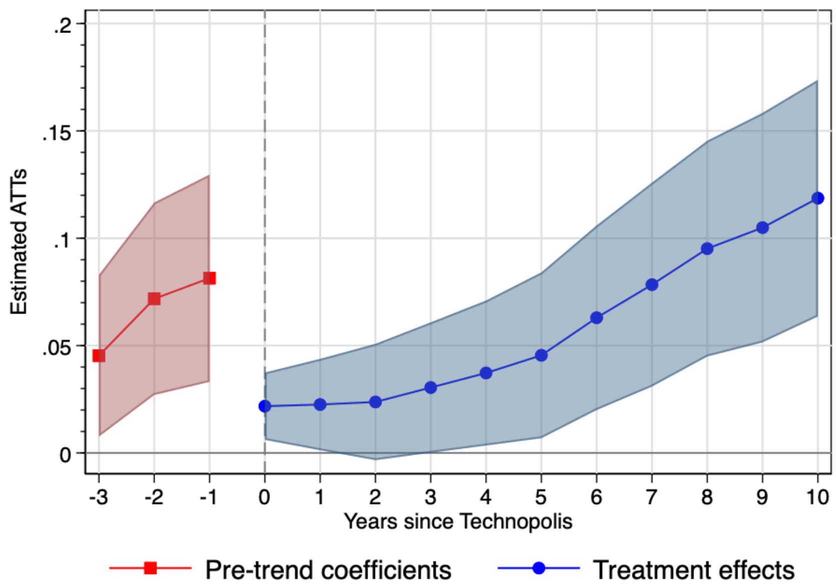
[19] To construct this city $\times$ 2-digit industry panel, we crosswalk the 2-digit manufacturing codes across the historical systems instituted in 1980, 1985, 2002, and 2008.

[20] While we observe PPE at the plant level in COM, we cannot aggregate up PPE to the city level due to changes across survey waves in the composition of plants which are required to report this information. In some years, plants with 10 or more employees are required to report PPE, while in other years only plants with 20 or more employees are required to report PPE.

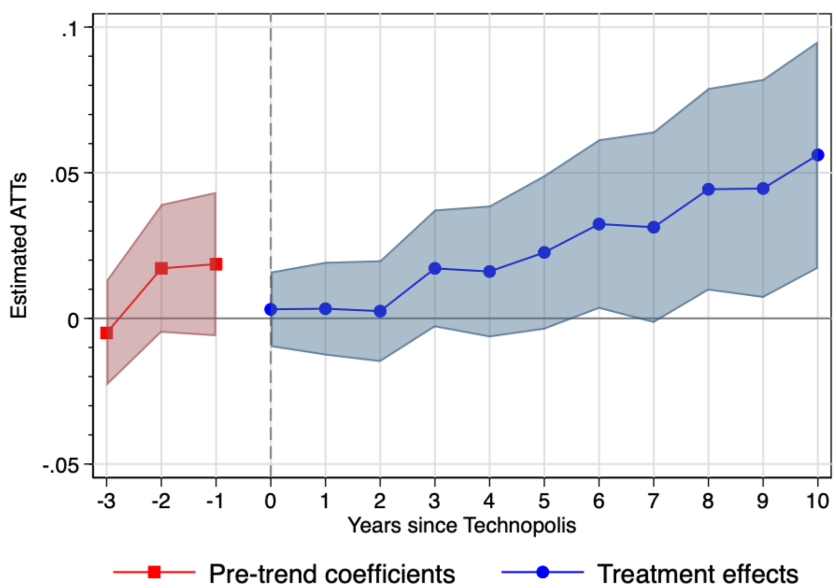
[21] See LaPoint (2021) for details on the appraisal data.

FIGURE 3. Dynamic City-level Responses to Technopolis Eligibility

A. Employment



B. Number of establishments



Notes: Each panel shows the dynamic response of an outcome of interest estimated via the staggered DD model in equation (4.2) using the imputation estimator method of Borusyak, Jaravel, & Spiess (2021). Panel A examines log of total employment among all manufacturing plants within the city, and Panel B examines the total number of manufacturing plants within the city. The point estimates allow for anticipatory effects one year in advance of the reform, so the coefficient at 0 years represents the one-year anticipatory effect. Our estimation sample is 1981 – 2000. Shaded regions contain 95% confidence intervals obtained from standard errors clustered at the municipality level. We impose modern municipality boundaries using the historical city code crosswalk available through RIETI (Kondo 2019). See text for details on the definition of each outcome.

5.2.1 Baseline Results

We start our firm-level analysis by presenting event study evidence from estimating equation (4.2), allowing for one-year anticipation of Technopolis eligibility, and again applying the *BJS* estimator for staggered DD designs. Figure 4 plots the dynamic effects $\widehat{\beta_t}$ of Technopolis eligbility for our six main outcomes of interest: the probability a firm claims bonus depreciation, cash flow (defined as net income before depreciation, after taxes paid), employment, construction in progress, the gross book value of new non-real estate assets (including precision tools + machinery + vehicles), and long-term debt issuance (the YOY increase in long-term loans payable). All event studies feature one-year leads on the β_t coefficients to capture one-year anticipatory effects, although we do not lead the coefficients to conduct our pre-trends testing in what follows.

We focus on bonus depreciation claiming on the extensive margin given that 77% of firm-years feature zero net income from bonus depreciation. We deflate monetary variables by the value for that firm in the filing year before our sample starts (1975). Hence, the effects are scaled so that $\widehat{\beta_t}$ captures the growth in a monetary variable relative to the pre-sample baseline that can be attributed to the firm becoming eligible for Technopolis bonus claims.[22]

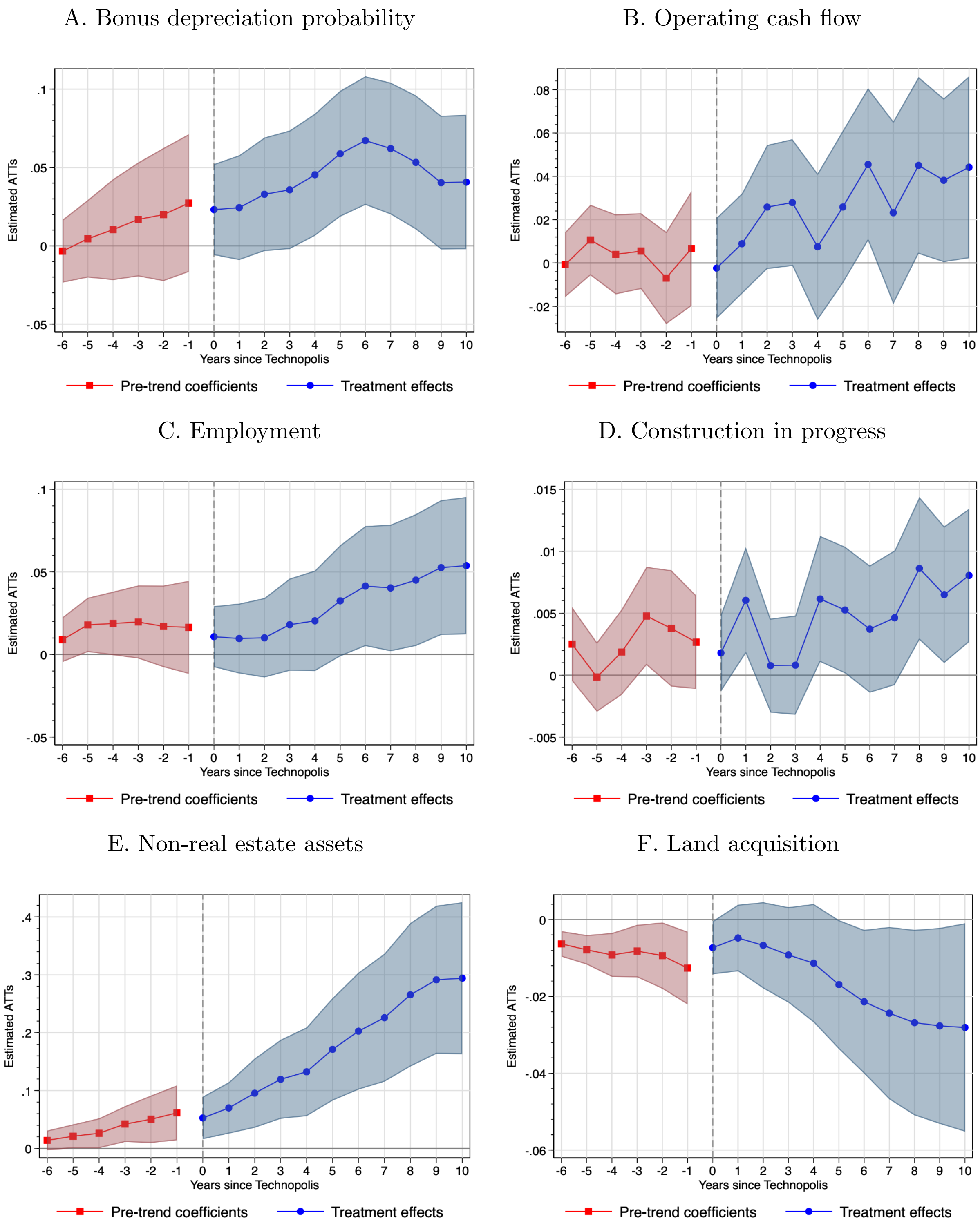
The first panel in Figure 4 shows the first stage of our research design by plotting how take-up of bonus depreciation incentives varies with respect to Technopolis eligibility. The propensity of eligible firms to increase their bonus claims steadily rises after the implementation date, with the effect peaking at 6.7 p.p. five years after enactment. Five years corresponds to a kink point in the tax schedule (Table 1), since firms can maximize their bonus rate if they invest within five years of the designated Technopolis area. While there is visual evidence of a pre-trend in our first stage (with the one-year anticipation), when we test for pre-trends by running a separate regression using untreated observations, we obtain a p-value of 0.694 on the hypothesis of joint significance of the loadings on the six lags.[23] The second panel shows that income from bonus claims begins to show up in firm cash flows several years into the Technopolis period, also spiking five years after eligibility.

Overall employment rises at treated firms by 5% (a 0.13 s.d. effect) relative to the level at the sample start date about 5 years into the reform, and the effect plateaus thereafter. We also find a clear upward trend in outlays for construction in progress, although due to the lumpiness of investment and frequent revision of construction costs for projects, these dynamic effects are volatile. Recall that while the Technopolis bonus rates for real estate investment are half those for non-real estate tangible investment, buildings are much longer-lived assets, and therefore offer a larger immediate cash flow benefit. The acquisition of non-real estate assets explodes and continues to grow until 9 years into the program. While part of this effect could be due to an inflationary

[22] As mentioned in Section 3.2, scaling by baseline assets accounts for skewness in the distribution of firm balance sheet variables. This scaling also has an advantage over taking logs for variables like debt issuance and cash flow which can be zero or negative.

[23] We augment the staggered DD model with linear firm time trends in Appendix E and show estimates under OLS and Sun & Abraham (2021). With the exception of employment, the estimated effects are stronger for our other main outcomes with linear trends, although the trends are not well-identified under the imputation method of *BJS*.

FIGURE 4. Dynamic Firm Responses to Technopolis Eligibility



Notes: Each panel shows the dynamic response of an outcome of interest estimated via the staggered DD model in equation (4.2) using the imputation estimator method of Borusyak, Jaravel, & Spiess (2021). Each regression includes HQ Census region × year fixed effects. With the exception of the bonus depreciation dummy and employment, each variable is deflated by the firm's book assets in 1975 before our estimation sample start date. Firm employment is scaled by its value in 1975. The point estimates allow for anticipatory effects one year in advance of the reform, so the coefficient at 0 years represents the one-year anticipatory effect. Shaded regions contain 95% confidence intervals obtained from standard errors clustered at the firm level. See text for details on the definition of each outcome.

component to new acquisitions rather than a real response, our models include both time and region $\times$ year fixed effects, which differences out national and semi-local pricing trends. Firms substitute away from investment in land (a 0.11 s.d. decline), which does not depreciate and thus becomes more expensive relative to other types of capital after the reform.[24]

The investment responses in Figure 4 are economically sizeable. The peak effect of Technopolis eligibility on non-real estate assets is 0.29 which is 40% of the standard deviation of gross book non-real estate assets. Similarly, for construction, the effect peaks at 0.009 which is 29% of the standard deviation of construction in progress. Importantly, while purchases of many types of non-real estate assets are reversible local investments, to the extent that the parent firm can sell or easily transport machines and other equipment away from the treated plant, construction of new structures or adding onto existing ones is not a reversible expense (at least not in the short-run). Technopolis was therefore successful relative to place-based tax breaks like the recent Foxconn Wisconsin case study in our Introduction at incentivizing firms not to "toe dip."

Table 5 establishes the robustness of our results to the inclusion of a battery of controls for time-invariant firm characteristics interacted with year fixed effects, other common cash flow measures such as EBITDA and operating cash flow (OCF), and Tobin's Q.[25] To render the effect sizes easier to interpret, we present results using log outcomes for employment and monetary variables. Overall, our first stage effect of eligibility on bonus claiming (Panel A) is stable across estimators and the inclusion of financial controls and region, size, and age-specific trends.

Comparing the point estimates in Panel B of Table 5 from estimating model (4.1) by OLS vs. the *BJS* estimator demonstrates the role that treatment effect heterogeneity plays in our setting. We find a 16.6 log points effect on construction outlays when we use OLS to estimate the staggered DD model (column 1), but a 21.2 log points effect when we estimate the same model via *BJS*. We present in Appendix E our results using other popular staggered DD estimators which address concerns about treatment effect heterogeneity. We consider the estimators of de Chaisemartin & D'Haultfœuille (2020) and Sun & Abraham (2021) and compare the dynamic treatment effects to those obtained under OLS and *BJS*. Among these non-OLS estimators, our results are qualitatively and quantitatively similar.

Although it weakens our results, in Table 5 we still uncover positive responses of bonus claiming, construction, and non-real estate acquisitions after including time-varying financial controls. While common in the empirical corporate finance literature, controls like EBITDA, OCF, and Q are "bad controls" in our setting because they are outcomes that may be directly influenced by Technopolis

[24]The p-values on the pre-trends tests for the other outcomes we consider in Figure 4 are 0.757 for operating cash flow, 0.313 for employment, 0.099 for construction, 0.204 for non-real estate investment, and 0.001 for land acquisition. Hence, with the exception of land investment, we find the parallel trends assumption to be valid.

[25]Note that we do not include 2-digit industry or sectoral fixed effects in our specifications. Industry fixed effects would be too fine of a control in the sense that many treated Technopolis 4-digit industry codes fall under the same 2-digit category (e.g. the 2-digit non-ferrous metals industry contains the copper smelting and electric wire 4-digit industries, both of which are eligible). Including a 2-digit fixed effect in this instance would thus mean differencing out the impact of Technopolis on two similar treated units, leading to an estimated null effect.

eligibility. In particular, OCF includes cash flow from bonus claims, so it is mechanically related to the take-up behavior induced by Technopolis.[26]

5.2.2 Local Spillovers of Technopolis

Did Technopolis generate local spillovers to untreated firms? Answering this question is important for assessing the local general equilibrium consequences of place-based tax incentives. One might imagine that by stimulating investment among high-tech intermediate goods firms in these areas, local firms in downstream industries might benefit from cheaper inputs or productivity gains from innovation. Our original specification in (4.1) is silent on this question, so we instead run an augmented model which includes an additional term to isolate the effect of being located in an eligible area but not satisfying the industry criteria for bonus claims:

$$y_{j,c,k,t} = \gamma_j + \delta_t + \beta_1 \cdot Treatment_{j,k,t} + \beta_2 \cdot TreatedCity_{j,c,t} + \eta' \cdot \mathbf{X}_{j,k,t} + \varepsilon_{j,c,k,t} \tag{5.1}$$

where $Treatment_{j,k,t}$ is defined as in Section 4 (i.e. it is equal to unity if all three eligibility criteria apply). The new dummy $TreatedCity_{j,c,t}$ is equal to unity if firm j controls a plant located in a Technopolis eligible area and t is greater than the minimum eligibility year across all eligible *cities* represented within the firm's 1980 internal network. That is, $TreatedCity_{j,c,t}$ is equal to one if the firm satisfies the first and last criteria, but not the second criterion listed Section 4.

Table 6 provides results from estimating this spillover regression for our four main outcomes of interest: extensive margin bonus claiming, and the logs of construction investment, non-real estate assets, and employment.[27] The first two columns using the bonus claim dummy as the outcome act as a placebo test: firms for which $TreatedCity_{j,c,t} = 1$ are not eligible to claim the bonus write-off, even though they have a presence at a Technopolis site. Reassuringly, we find no significant uptick in bonus claims among local untreated firms. We find evidence of negative spillovers for non-real estate assets; firms in ineligible industries located in an active Technopolis site experienced a reduction in their non-real estate PPE of between 10% and 12%. The negative spillover to untreated firms is of a similar magnitude with the full set of controls, meaning that it exists even when comparing two firms with an HQ in the same region of the country and within the same size and age quintiles. Given that wholesale price indices for non-real estate assets vary minimally across regions during this time period, our finding is unlikely to be a mechanical consequence of the late 1980s boom-bust cycle. This suggests Technopolis may have crowded out non-real estate physical investment among ineligible incumbent firms.

---

[26] See Lian & Ma (2021) for a discussion on how to construct operating cash flow (OCF) and how it differs from EBITDA. For our purposes, the main distinction between the two cash flow measures is that net income from bonus depreciation write-offs will be reflected in OCF but not in EBITDA. Indeed, when we estimate (4.2) with OCF as the outcome variable (Panel B of Figure 4), we find cash flows peak at years 5 and 7 after the reform, which corresponds to the first two kink points in the bonus depreciation schedule in Table 1.

[27] We plot the dynamic effects of the *Treatment* and *TreatedCity* dummies in Appendix F.

TABLE 5. Bonus Claim, Investment, and Employment Responses to Technopolis

A. First stage: extensive margin bonus depreciation claims

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.091***	0.072**	0.086***	0.094***	0.070**	0.090***
	(0.028)	(0.029)	(0.027)	(0.028)	(0.030)	(0.028)
Estimator	OLS	OLS	OLS	*BJS*	*BJS*	*BJS*
Firm FEs	✓	✓	✓	✓	✓	✓
Financial controls		✓			✓	
Controls × year FEs			✓			✓
N	38,374	34,578	38,360	38,374	34,578	38,360
# Firms	1,508	1,408	1,507	1,508	1,408	1,507
Adj. R^2	0.535	0.547	0.551	0.535	0.547	0.551

B. Investment and employment responses

	Construction			Non-RE assets			Employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	0.166**	0.111*	0.221***	0.184***	0.145***	0.189***	0.070**	0.035	0.074**
	(0.072)	(0.067)	(0.077)	(0.046)	(0.039)	(0.046)	(0.030)	(0.028)	(0.032)
Estimator	OLS	*BJS*	*BJS*	OLS	*BJS*	*BJS*	OLS	*BJS*	*BJS*
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Financial controls		✓			✓			✓	
Controls × year FEs			✓			✓			✓
N	26,996	24,408	26,985	36,396	32,829	36,383	38,340	34,578	38,326
# Firms	1,416	1,318	1,415	1,499	1,399	1,498	1,508	1,408	1,507
Adj. R^2	0.702	0.723	0.702	0.948	0.957	0.949	0.954	0.964	0.955

Notes: The table shows results from estimating our staggered DD model in equation (4.1) at the firm level for our main outcomes of interest, pooling all years (1975–2000). The outcome in Panel A is a dummy equal to one if the firm receives net income from bonus depreciation in a given year. In Panel B, construction is the log book value of construction in progress, non-RE assets is the log gross book value of PPE excluding buildings, land, and structures, and employment is the the log number of employees. Controls include static factors such as the size quintile (by total assets), quintile of age measured from the Tokyo Stock Exchange listing date, and Census region of the HQ, all interacted with a full set of year dummies. Specifications with financial controls include EBITDA, OCF, and the Q ratio as time-varying controls. EBITDA and OCF are defined using standard accounting principles. The Q ratio is the ratio of the market value of the firm (total assets + market equity − common equity − deferred tax payments relative to book assets). Standard errors clustered at the firm level are in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

TABLE 6. Local Spillovers of Technopolis via Untreated Firms

	Bonus claim		Construction		Non-RE assets		Employment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.100***	0.084***	0.139*	0.145*	0.151***	0.136***	0.080**	0.076**
	(0.028)	(0.028)	(0.074)	(0.074)	(0.047)	(0.047)	(0.031)	(0.030)
TreatedCity	0.029	−0.004	−0.087	−0.083	−0.105***	−0.129***	0.029	0.014
	(0.016)	(0.017)	(0.065)	(0.068)	(0.033)	(0.036)	(0.021)	(0.022)
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls × year FEs		✓		✓		✓		✓
N	38,374	38,360	26,996	26,985	36,396	36,383	38,340	38,326
# Firms	1,508	1,507	1,416	1,415	1,499	1,498	1,508	1,507
Adj. R^2	0.535	0.551	0.702	0.702	0.948	0.949	0.954	0.955

Notes: The table shows results from estimating the spillover model in equation (5.1) at the firm level for our main outcomes of interest. Bonus claim is a dummy equal to one if the firm receives net income from bonus depreciation in a given year, construction is the log book value of construction in progress, non-RE assets is the log gross book value of PPE excluding buildings, land, and structures, and employment is the the log number of employees. Controls include static factors such as the size quintile (by total assets), quintile of age measured from the Tokyo Stock Exchange listing date, and Census region of the HQ, all interacted with a full set of year dummies. Standard errors clustered at the firm level are in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

5.2.3 Trade (Non-)Spillovers of Technopolis

While we found no evidence of local spillovers to ineligible firms, it is possible that both eligible and ineligible firms' hiring and investment decisions were influenced by inter-regional trade linkages to firms in eligible sectors operating in Technopolis areas. For example, manufacturers of woodworking machines, an industry eligible for Technopolis, may pass along reduced capital costs to ineligible furniture makers, leading the latter to increase hiring or CAPX. This would be an example of indirect trade spillovers through imports, or a supply chain channel. Conversely, for the woodworking machine manufacturers there could be amplification of the direct effects of bonus eligibility because their Technopolis eligible customers are looking to expand, and therefore will demand more machines as an intermediate input. This would be an example of indirect trade spillovers through an export demand channel.

To test for the presence of such trade spillovers, we augment our baseline event study specification in equation (4.2) to include leads and lags of a firm's exposure to inter-regional trade. We adapt the approach of Siegloch, Wehrhöfer, & Etzel (2021) to our setting, which takes imports originating from prefecture q (alternatively, exports to q) by each sector k located in prefecture p, and divide that number by total imports (exports) of the prefecture pair × sector cell. We then interact these prefecture pair × sector import and export shares with a treatment dummy equal to one if prefecture

q contains one of the 26 regional Technopolises.[28] Finally, after summing up all the interaction terms, we convert the resulting regional measure of trade exposure to a firm-level measure by taking a weighted average across all prefectures where the firm operates an establishment. We use as weights the share of 1980 firm book PPE located at prefecture p; hence, the weights will be zero if the firm does not have a 1980 presence in p.[29]

Our procedures can be summarized by the following sequence of equations:

$$y_{j,k,t} = \gamma_j + \delta_t + \sum_{t=1,t\neq t_0}^{T} \beta_{1,t} \cdot Treatment_{j,k,t} + \sum_{t=1,t\neq t_0}^{T} \beta_{2,t} \cdot TradeExposure_{j,k,t} + \varepsilon_{j,k,t} \tag{5.2}$$

$$\text{with} \quad TradeExposure_{j,k,t} = \sum_{p\in\mathcal{J}} \omega^{j}_{p,1980} \cdot TradeExposure^{k}_{p,t} \quad \text{for } \mathcal{J} = \{1, 2, \ldots, n\}$$

$$\text{where} \quad \omega^{j}_{p,1980} = \frac{PPE^{j}_{p,1980}}{\sum_{p\in\mathcal{J}} PPE^{j}_{p,1980}}$$

$$\text{and} \quad \text{TradeExposure}^{k}_{p,t} = \underbrace{\sum_{q\neq p} \frac{Imports^{k}_{p,q}}{TotalImports^{k}_{p}} \times Treatment_{q,t}}_{\text{supply}} + \underbrace{\sum_{q\neq p} \frac{Exports^{k}_{p,q}}{TotalExports^{k}_{p}} \times Treatment_{q,t}}_{\text{demand}} \tag{5.3}$$

where equation (5.2) describes our augmented event study model, which uses firm-level trade exposure obtained from aggregating the prefecture $\times$ sector exposure measure in (5.3) by taking a PPE share-weighted average across all prefectures in the firm's network of locations spanned by the set $\mathcal{J}$. We also estimate separate versions of (5.2) where we use only the "supply" or only the "demand" components which link a firm to other firms across the country through trade.

Figure 5 plots the estimated direct effects represented by $\widehat{\beta}_{1,t}$ and the indirect effects $\widehat{\beta}_{2,t}$ for the import and export exposure measures from (5.2) and (5.3). For each of our main outcomes, the evolution of the direct effects of Technopolis eligibility (red) are virtually identical in magnitude to the baseline effects reported in Figure 4. At the same time, we find no effects of indirect exposure through trade linkages regardless of whether we examine import/supply (Panel A) or export/demand shocks (Panel B); the confidence intervals are quite large for the loadings on both types of shocks, and there is no clear trend in the point estimates.[30] We conclude that while targeted bonus incentives may have helped stimulate local labor and capital markets, these responses did not propagate through inter-regional trade networks for corporations.

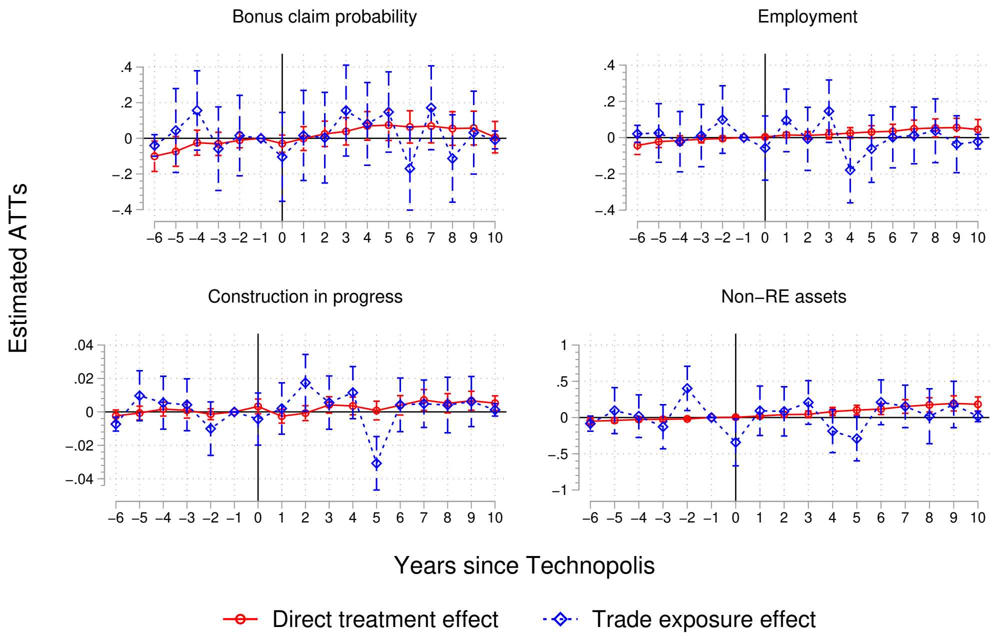
[28] We use the R-JIP database from 2005 which provides the prefectural input-output matrix denominated in yen for 26 industrial sectors. In constructing the prefecture pair $\times$ industry $TradeExposure$ measures in (5.3), we sort these sectors on the basis of whether they contain 4-digit JSICs which are eligible for bonus claims through Technopolis. The trade matrices are can be downloaded at https://www.rieti.go.jp/jp/database/R-JIP2005/index.html.

[29] Our results are unchanged if we instead weight by employment across plant locations in 1980, or if we define the treatment dummy in the trade exposure measure at the prefecture $\times$ sector cell.

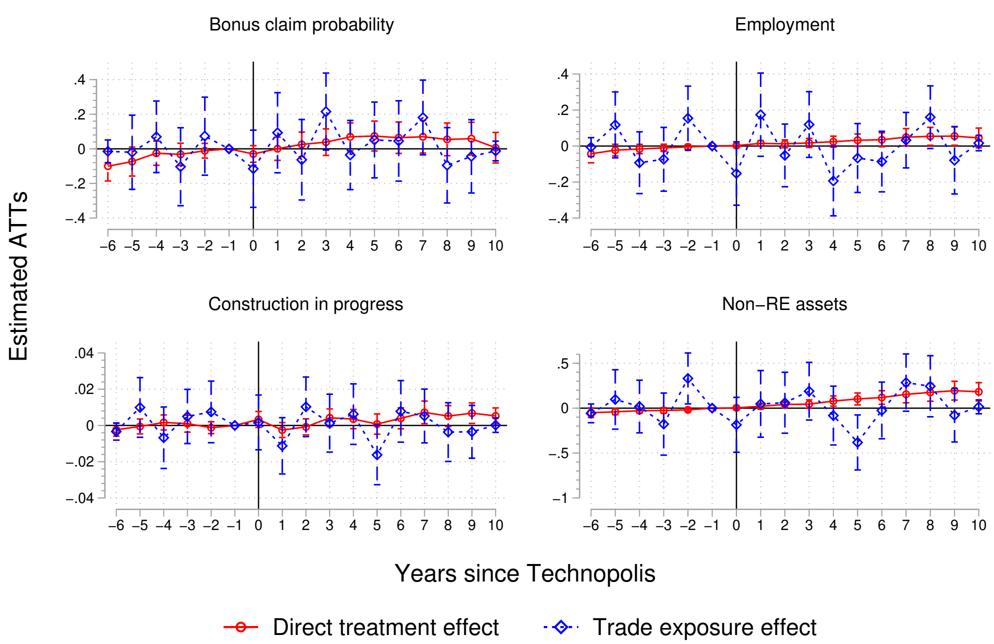
[30] Summing up the import and export exposure measures, as we do in (5.3), also produces very imprecise estimates and no clear monotonicity following policy implementation.

FIGURE 5. Non-evidence of Exposure to Technopolis through Inter-regional Trade

A. Import exposure (supply)



B. Export exposure (demand)



Notes: Each panel shows the dynamic response of an outcome of interest estimated from the staggered DD model of (5.2) via OLS, with eligibility dummies (blue) and leads/lags of the indirect trade exposure measure (red). We report separate indirect trade effects for imports (Panel A) and exports (Panel B). Each regression includes HQ Census region × year fixed effects. Construction in progress and non-real estate assets are deflated by the firm's book assets in 1975 before our estimation sample start date. Firm employment is scaled by its value in 1975. We bin the dummies at the end of the effect windows for $t = -6$ and $t = 10$. All dynamic effects are relative to one year before Technopolis eligibility begins. The bars show 95% confidence intervals obtained from standard errors clustered at the firm level.

5.3 Heterogeneous Firm Responses

We now examine heterogeneous responses to the Technopolis policy based on firms' pre-existing physical capital structure and the extent to which bonus claims have the potential to relieve financing constraints on CAPX.

5.3.1 Long vs. Short-lived Capital Shares

Recall the example from Section 2.1 of a firm purchasing a new office building and computers to staff a site in a Technopolis-eligible area. Since the typical office site can be depreciated over 50 years, while computers can only be depreciated over 4 years, a firm relying more on long-lived assets like buildings will be better able to extract cash flow from the future to the present through bonus claims. That is, we expect take-up, investment, and hiring responses to be more pronounced among firms which have a more long-lived physical capital structure. We test this hypothesis by constructing a measure – informed by the Q-theory of investment – to rank firms based on their reliance on short-lived vs. long-lived assets.

Following the methods in Hayashi (1990) and Hayashi & Inoue (1991), we recover shares for each input in a firm's physical capital stock used towards production. We apply this method to the DBJ data on listed firms to sort firms based on their reliance on long-lived vs. short-lived capital. The plant-level Census only decomposes tangible assets into land, buildings, machinery, and a residual other category. At the same time, we cannot compute other parameters such as the weighted average cost of capital (WACC) and corporate income tax bill which are necessary for the calculations. Therefore, in this exercise we focus on the sample of listed firms which we can match to plants reported in the manufacturing Census.

The complete algorithm steps are described in LaPoint (2021), but we provide a brief outline here for convenience. The economic intuition underlying the approach is that a profit-maximizing firm will set the marginal rate of substitution between any two capital goods equal to the ratio of the goods' user costs. In addition to profit maximization, recovery of the capital input shares relies on two assumptions:

(i) The profit function is homogeneous of degree one in the capital inputs k_i, where here $i = 1, \ldots 6$ and the capital goods categories are buildings, land, structures, machines, precision tools, and transportation vehicles. We exclude inventories from the decomposition since our data are not itemized to the extent that we can separate inventories into inputs and outputs. Even though land does not depreciate, we include it in the capital aggregator because land is a complementary good to buildings and outdoor structures (e.g. wells, sheds, encampments).

(ii) There is a capital aggregator $f(K_j)$ for each firm j, which is homogeneous of degree one in each of the goods $k_{i,j}$. For tractability, we make the additional assumption that the aggregator is constant returns to scale, or:

$$f(K_j) = \prod_{i=1}^{6} k_i^{\omega_{i,j}} \quad \text{s.t.} \quad \sum_{i=1}^{6} \omega_{i,j} = 1, \forall j \tag{5.4}$$

Armed with these two assumptions, for each firm we compute the input shares $\omega_{i,j}$ by iterating on the system of equations consisting of the full set of tangency conditions implied by profit maximization together with equation (5.4). Implicitly we are assuming the functional form $f(\cdot)$ to be exogenous and fixed. Since it is possible that offering tax incentives for investment in long-lived assets might induce firms to alter their mix of inputs, we compute the shares $\omega_{i,j,t}$ for each year and then take the average shares over the pre-reform period 1975 – 1983.[31]

This structural method based on firm profit maximization generates input share distributions which are broadly in line with the mix of intermediate goods used by each 2-digit industrial sector. For instance, heavy manufacturing firms have an average machine input share of 0.24, while this is only 0.18 for agricultural and 0.17 for services firms. Although this approach has the advantage of being motivated by theory and relying on transparent assumptions, one downside is that it requires firms to have non-missing values for corporate income tax payments to identify user costs in the first-order conditions of the firm's problem. As such, we can only directly recover input shares for roughly one-third of DBJ firms; this subsample spans all 2-digit industry codes in the full sample. To overcome this issue, we apply a nearest-neighbor matching algorithm where we assign firms with missing input shares the input shares of a donor firm with the smallest distance in propensity scores. We provide more details on the imputation procedure and statistics of input shares for each capital good in Appendix D.

We then run the following regression which tests for differential effects of the Technopolis policy depending on whether the firm relies on a larger share of long-lived capital inputs to production:

$$\begin{aligned} y_{j,t} = \gamma_j + \delta_t + \beta_1 \cdot Treatment_{j,t} \times LL - Firm_j \\ + \beta_2 \cdot Treatment_{j,t} \times SL - Firm_j + \eta' \cdot \mathbf{X}_{j,t} + \varepsilon_{j,t} \end{aligned} \tag{5.5}$$

where $Treatment_{j,t}$ is defined at the firm level based on whether the firm is in an eligible industry and has a presence in a Technopolis area after the minimum possible implementation date. Here we suppress the k industry subscript for ease of exposition. We define the dummy $LL - Firm_j$ ("long-lived") as equal to unity if firm j has an *ex ante* share of building inputs ω_{build} above the median value across all firms. Similarly, $SL - Firm_j$ ("short-lived") is equal to one if the firm has an *ex ante* value for ω_{build} below the median. In some specifications, we include the usual set of time-invariant firm characteristics interacted with year dummies in $\mathbf{X}_{j,t}$, so the comparison is

[31] The input shares for long-lived assets decline in the 1990s. This is reflected in the fact that while we find growth in both the stock of new construction and non-real estate assets – which are complementary inputs under the aggregator in (5.4) – we find that YOY investment in long-lived assets falls after the early 1990s crash.

TABLE 7. Firm-level Results by Long-lived Asset Share

	Bonus claim		Construction		Non-RE assets		Employment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treatment \times LL - Firm$	0.096***	0.089***	0.166**	0.170**	0.180***	0.171***	0.077**	0.076**
	(0.029)	(0.028)	(0.074)	(0.074)	(0.048)	(0.049)	(0.031)	(0.031)
$Treatment \times SL - Firm$	−0.011	0.028	0.169	0.160	0.245**	0.265***	−0.037	−0.004
	(0.104)	(0.109)	(0.261)	(0.273)	(0.097)	(0.094)	(0.111)	(0.106)
p-value on difference	0.319	0.586	0.991	0.971	0.542	0.367	0.323	0.465
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls × year FEs		✓		✓		✓		✓
N	38,374	38,360	26,996	26,985	36,396	36,383	38,340	38,326
# Firms	1,508	1,507	1,416	1,415	1,499	1,498	1,508	1,507
Adj. R^2	0.535	0.551	0.702	0.702	0.948	0.949	0.954	0.955

Notes: The table shows results from estimating equation (5.5) at the firm level for our main outcomes of interest. Bonus claim is a dummy equal to one if the firm receives net income from bonus depreciation in a given year, construction is the log book value of construction in progress, non-RE assets is the log gross book value of PPE excluding buildings, land, and structures, and employment is the the log number of employees. Controls include static factors such as the size quintile (by total assets), quintile of age measured from the Tokyo Stock Exchange listing date, and Census region of the HQ, all interacted with a full set of year dummies. We use the pre-Technopolis share of buildings in the firm's constant returns to scale production function as the basis for classifying firms as using primarily long-lived or short-lived assets. See text and Appendix D for details on how we construct capital input shares. Standard errors clustered at the firm level are in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

between firms with HQs in the same Census region, and operating within the same size bin, age bin, and main bank cell, which differ on city × industry eligibility to participate in Technopolis.

We define $LL - Firm_j$ and $SL - Firm_j$ according to the share of building inputs due to the incredibly long-lived nature of commercial buildings in the tax code. An alternative would be to categorize the six capital goods we observe in the DBJ data by their average linear depreciation rate, assuming firms use a straight-line depreciation accounting method. This can be accomplished by comparing accumulated depreciation for each PPE category to gross book value to back out average asset age for goods type. This exercise yields a depreciation life of 25 years for buildings, 15 years for machines, 11 years for tools, and 10 years for transportation.[32] Hence, we could then lump buildings and machines into one category of long-lived assets, and group the remaining CAPX categories together as short-lived assets. We do not take this approach because non-real estate assets are very heterogeneous in the tax code in terms of their depreciation lives. For example, within the machines category depreciation lives vary from 3 years for electricity boards used in the textile dyeing industry to 25 years for starch processing machines used in the agricultural industry.

[32]This 4% linear rate of depreciation is about half of what Yoshida (2020) finds via a hedonic model approach using CRE transactions, suggesting that bonus claims among listed firms are disproportionately applied towards investment in buildings. A 2% rate is consistent with the Japanese tax code wherein CRE buildings typically have depreciation lives between 50 and 60 years.

Table 7 provides evidence in favor of the notion that long-lived asset firms were more likely to claim and use bonus cash flows under the Technopolis regime. The first column shows bonus claim probability increased by 9.6 p.p. for long-lived asset firms, but not at all for short-lived asset firms. Firms relying more on properties also employed more workers in response to Technopolis eligibility. On the other hand, the difference between $\widehat{\beta_1}$ and $\widehat{\beta_2}$ in equation (5.4) is never statistically significant; this is driven by the large standard errors on the point estimates for the effect of treatment on short-lived asset firms.[33] One possibility is that long-lived asset firms stand to gain less from bonus depreciation because they already rely on declining balance accounting, which allows firms to extract more cash flow earlier in the asset's life, in exchange for small tax write-offs later on. Yet, when we compare firms who rely entirely on declining balance vs. straight-line depreciation methods we find they have statistically identical ω_{build}, with an average of 0.47 in each subgroup.[34]

5.3.2 The Role of Financing Constraints

Previous work in spatial corporate finance has argued that multi-plant firms are more likely to rely on internal capital markets to smooth out shocks if they are financially constrained (e.g. Giroud & Mueller 2015). In our context, a natural question is whether the real responses to the Technopolis bonus depreciation scheme documented in this section are driven by *ex ante* constrained firms, for which the immediate cash flow benefits may have a higher marginal value. We find that the answer to this question is yes – both in terms of the firms who claim the benefit and those which engage in more new construction and hiring within treated industry-location cells.

We use several indexes popular in the corporate finance literature to rank firms from least constrained to most constrained as of the last year prior to the first implementation of a Technopolis area (1983). Our main measure, and the one most commonly cited in recent work, is the size-age index of Hadlock & Pierce (2010) [HP] which ranks firms according to:

$$-0.737 \cdot Size + 0.043 \cdot Size^2 - 0.040 \cdot Age$$

where *Size* refers to the log of inflation-adjusted total assets, and *Age* is the number of years the firm has been listed as of 1983.[35] In addition to the Hadlock-Pierce index, we also consider

[33] We plot the dynamic effects of the $LL - Firm$ and $SL - Firm$ dummies in Appendix F.

[34] We also checked whether a simple above/below median split inherent in equation (5.4) is masking non-linear effects across the distribution of ω_{build}. We uncover a U-shaped pattern when we re-estimate versions of (5.4) where we interact $Treatment_{j,t}$ with dummies indicating the quintile of ω_{build}. For example, bonus claiming probability increases by 16 p.p. for firms in the bottom quintile with $\omega_{build} < 0.27$, and by 15 p.p. for firms in the top quintile, with no statistically significant response in the middle of the building share distribution.

[35] In the original HP index, *Size* and *Age* are capped at 4.5 billion USD and 37 years, respectively. Given that firms in the DBJ sample are older than the typical sample of COMPUSTAT firms, we also test additional calibrations where we do not censor the *Age* and *Size* variables and using age measured from the time of establishment rather than the listing date. We find our results virtually unchanged for these alternative versions of the index, which supports the argument in Hadlock & Pierce (2010) that for the largest and oldest firms there ceases to be any relation between financing constraints and balance sheet size or age.

the Kaplan-Zingales [KZ] index and the Whited-Wu [WW] index. The KZ index is virtually uncorrelated with WW and HP, while the WW index is highly negatively correlated (-69%) with HP in the cross-section of firms. Given the evidence in LaPoint (2021) that the HP index is a robust predictor of debt issuance sensitivity to collateral values, we are confident that the HP index is an appropriate proxy for the external financing access of Japanese firms.

Similar to the specification in (5.3) comparing firms with long-lived vs. short-lived capital inputs, we estimate the following equation which allows for differential effects of the Technopolis policy depending on financing constraints:

$$y_{j,t} = \gamma_j + \delta_t + \beta_1 \cdot Treatment_{j,t} \times FC_j + \beta_2 \cdot Treatment_{j,t} \times NFC_j + \eta' \cdot \mathbf{X}_{j,t} + \varepsilon_{j,t} \tag{5.6}$$

where $Treatment_{j,t}$ is defined analogously to the previous specifications (i.e. based on whether the firm is in an eligible industry and has a presence in a Technopolis area after the implementation date). We suppress the industry subscript for simplicity. We define the dummy FC_j ("financially constrained") as equal to unity if firm j has an *ex ante* HP index value above the median value across all firms. Similarly, NFC_j ("non-financially constrained") is equal to one if the firm has an *ex ante* HP index value below the median. We include the usual set of baseline characteristics interacted with year dummies in the vector $\mathbf{X}_{j,t}$.

The results in Table 8 show that our findings of economically significant investment and employment responses are indeed driven by financially constrained firms and not by unconstrained firms. Bonus depreciation claim probability increased by 12.2 p.p. for constrained firms after Technopolis eligibility kicked in, with a 21.4% increase in construction outlays, a 34.6% increase in non-real estate assets, and 13.7% increase in employment. In contrast, the loading on $Treatment \times NFC$ is never statisticallly significant across all four outcomes, regardless of whether we saturate the model with non-parametric trends. While we cannot reject the null that $\widehat{\beta}_1$ and $\widehat{\beta}_2$ are equivalent for construction, we can reject the null of equivalent non-real estate acquisition (p-value $= 0.003$) and employment responses across the two groups (p-value $= 0.024$). Overall, Table 8 suggests financially constrained firms were more likely to claim the cash flow benefit provided by the Technopolis policy.[36] Financially constrained firms then used the funds to finance construction and non-real estate purchases and hire more employees.

5.4 Separating Multiple Policy Treatments

Our main results center on the effects of the Technopolis policy, which targeted the physical capital-intensive manufacturing firms that are more likely to benefit from extracting immediate cash flow from long-lived assets. The Japanese government introduced the Intelligent Location policy between 1989 and 1994 in an attempt to accelerate the industry clusters of Technopolis by expanding the catchment areas and extending bonus incentives to firms engaged in high-tech services (e.g.

[36] We plot the dynamic effects of the FC and NFC dummies in Appendix F.

TABLE 8. Firm-level Results by Ex Ante Financing Constraints

	Bonus claim		Construction		Non-RE assets		Employment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treatment \times FC$	0.122***	0.096***	0.194**	0.195**	0.297***	0.256***	0.128***	0.087**
	(0.038)	(0.037)	(0.089)	(0.093)	(0.049)	(0.051)	(0.036)	(0.036)
$Treatment \times NFC$	0.050	0.054	0.120	0.122	0.038	0.044	−0.004	0.024
	(0.040)	(0.040)	(0.109)	(0.116)	(0.085)	(0.084)	(0.048)	(0.050)
p-value on difference	0.186	0.441	0.583	0.616	0.003	0.016	0.024	0.299
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls × year FEs		✓		✓		✓		✓
N	38,374	37,845	26,996	26,529	36,396	35,885	38,340	37,811
# Firms	1,508	1,507	1,416	1,411	1,499	1,498	1,508	1,507
Adj. R^2	0.535	0.555	0.702	0.702	0.948	0.950	0.954	0.956

Notes: The table shows results from estimating equation (5.6) at the firm level for our main outcomes of interest. Bonus claim is a dummy equal to one if the firm receives net income from bonus depreciation in a given year, construction is the log book value of construction in progress, non-RE assets is the log gross book value of PPE excluding buildings, land, and structures, and employment is the the log number of employees. Controls include static factors such as the size quintile (by total assets), quintile of age measured from the Tokyo Stock Exchange listing date, Census region of the HQ, and the main bank identifier, all interacted with a full set of year dummies. We use an uncensored HP index to classify firms as financially (un)constrained. Standard errors clustered at the firm level are in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

software) and precision instruments manufacturing. Due to the spatial overlap of Technopolis and Intelligent Location (cf. Figure 2), and the fact that Intelligent Location industries were in many cases downstream of the industries eligible under Technopolis (cf. Appendix B), the two policies may have cross-pollinated each other. For instance, manufacturing companies who invested under a qualifying Technopolis may in turn realize productivity gains from software companies expanding their operations in an overlapping Intelligent Location. Such productivity gains would then be reflected in the employment and investment outcomes we consider in estimating regressions like equation (4.1), as firms set the marginal products of capital and labor equal to real input costs.

To assess the extent to which the dynamic effects exhibited in Figure 4 may reflect such local general equilibrium effects, we augment our baseline staggered DD specification to account for firms' eligibility under the Intelligent Location criteria:

$$y_{j,k,t} = \gamma_j + \delta_t + \beta_1 \cdot Treatment^{T}_{j,k,t} + \beta_2 \cdot Treatment^{IL}_{j,k,t} + \eta' \cdot \mathbf{X_{j,k,t}} + \varepsilon_{j,k,t} \tag{5.7}$$

where $Treatment^{T}_{j,k,t}$ is equal to one for firms eligible for bonus incentives under Technopolis, and $Treatment^{IL}_{j,k,t}$ is equal to one for firms eligible for the bonuses provided by Intelligent Location. Both treatment dummies are defined using the three-step procedure described in Section 4. The sets of firms eligible according to each policy are not disjoint; in our sample of 1,508 DBJ firms,

TABLE 9. Firm-level Results with Separate Policy Treatments

	Bonus claim		Construction		Non-RE assets		Employment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treatment^T$	0.093***	0.087***	0.163**	0.167**	0.172***	0.165***	0.060*	0.062**
	(0.028)	(0.028)	(0.072)	(0.072)	(0.046)	(0.047)	(0.031)	(0.030)
$Treatment^{IL}$	−0.023	−0.018	0.044	0.042	0.143**	0.138**	0.125***	0.119***
	(0.024)	(0.023)	(0.108)	(0.109)	(0.059)	(0.059)	(0.039)	(0.039)
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls × year FEs		✓		✓		✓		✓
N	38,374	38,360	26,996	26,985	36,396	36,383	38,340	38,326
# Firms	1,508	1,507	1,416	1,415	1,499	1,498	1,508	1,507
Adj. R^2	0.535	0.551	0.702	0.702	0.948	0.949	0.954	0.956

Notes: The table shows results from estimating equation (5.7) at the firm level for our main outcomes of interest. $Treatment^T$ refers to point estimates for the loading on Technopolis eligibility, and $Treatment^{IL}$ refers to point estimates for the loading on Intelligent Location eligibility. Bonus claim is a dummy equal to one if the firm receives net income from bonus depreciation in a given year, construction is the log book value of construction in progress, non-RE assets is the log gross book value of PPE excluding buildings, land, and structures, and employment is the the log number of employees. Controls include static factors such as the size quintile (by total assets), quintile of age measured from the Tokyo Stock Exchange listing date, Census region of the HQ, all interacted with a full set of year dummies. Standard errors clustered at the firm level are in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

31% ($N = 457$) are in a Technopolis treated industry, 18% ($N = 276$) are in a Intelligent Location treated industry, and 8% are in both ($N = 121$).

Table 9 provides results for our main outcomes of interest from estimating the multiple treatment regression in equation (5.7).[37] First, we observe that the estimates for β_1 are quantitatively similar to those reported in Panel B of Table 5. Thus, conditioning on receiving eligibility for Intelligent Location bonuses between 1989 and 1994 does not affect our estimates of the average effect of using Technopolis bonuses. Interestingly, we do not observe any significant effect of Intelligent Location eligibility on bonus claims or construction after conditioning on Technopolis eligibility. Yet, there is a positive and significant loading on Intelligent Location treatment for non-real estate assets (14.3 log points in column 5) and employment (12.5 log points in column 7). This makes intuitive sense, since Intelligent Location targeted specialized service sector firms which rely less on physical space and more on high-skilled labor and advanced technology. Even if IL-eligible firms did not increase their bonus claims (column 1), they may have increased their hiring and output in catchment areas to service proximal downstream firms who expanded under Technopolis.

Directly interpreting $\widehat{\beta_2}$ in Table 9 as a treatment effect of the Intelligent Location policy is complicated by the cross-contamination of treatment and control groups in regressions with multiple treatment dummies. de Chaisemartin & D'Haultfœuille (2021) analyze regressions like our equation

[37]We plot the dynamic effects of the $Treatment^T$ and $Treatment^{IL}$ dummies in Appendix F.

(5.7) and formally decompose the coefficient on one treatment dummy as the sum of two terms: (i) the weighted average effect of moving the first treatment from 0 to 1 while keeping the second treatment at its observed value, and (ii) the weighted average effect of moving the second treatment from 0 to 1 while keeping the first treatment at 0 across all group-time cells that receive the second treatment. That is, in our setting, both β_1 and β_2 are inclusive of treatment effects of the other policy for some subgroup of firms.

We adopt the approach recommended by de Chaisemartin & D'Haultfœuille (2021) for extending the estimator introduced in de Chaisemartin & D'Haultfœuille (2020) to isolate an unbiased estimate of the average treatment effect of moving $Treatment^{IL}$ from 0 to 1. Constructing this estimator involves running the following event study specification:

$$y_{j,k,t} = \gamma_j + \delta_t + \sum_{t=1, t \neq t_0}^{T} \beta_{2,t} \cdot Treatment^{IL}_{j,k,t} + F^{T}_{j,t} + \varepsilon_{j,k,t} \tag{5.8}$$

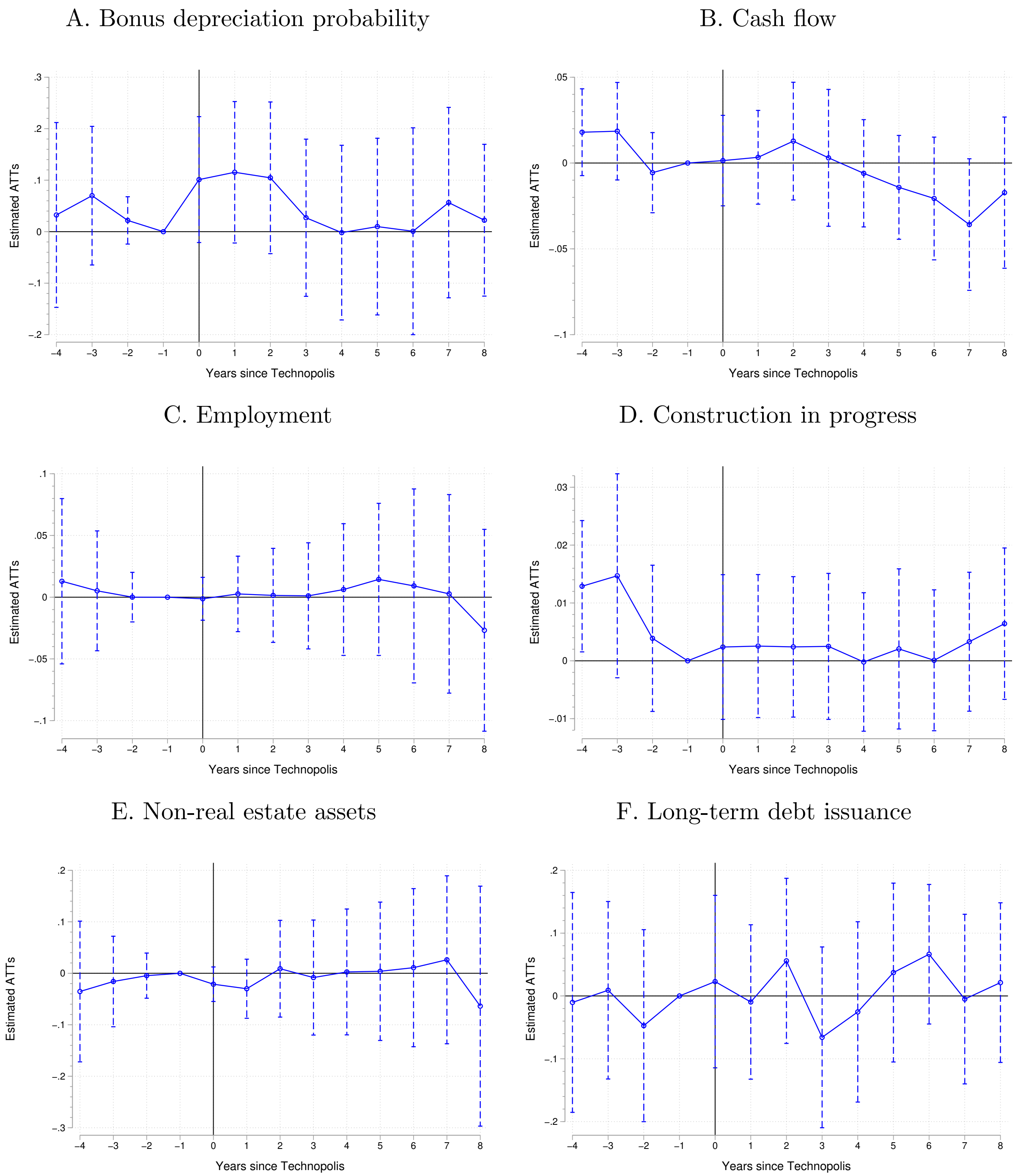
which mirrors our previous event study equation from Section 4, but with two key differences. First, we only estimate (5.8) on the set of firm-time observations such that $Treatment^{T}_{j,k,t} = 1$. Second, we include non-parametric trends $F^{T}_{j,t}$ with respect to the first year in which each firm becomes eligible to claim bonuses under Technopolis (i.e. under the first treatment). The resulting event study coefficients $\beta_{2,t}$ compare outcomes between firms that do vs. those that do not become eligible under Intelligent Location, but that became eligible for Technopolis at some prior date.[38]

Figure 5 plots the dynamic treatment effects of the Intelligent Location policy obtained from estimating the model in (5.8) for the subsample of firm-time observations which were directly treated by Technopolis. The figure tells a very different story than the regression results in Table 9. In particular, there is a clear, but imprecisely estimated, uptick in bonus claiming behavior of roughly 10 p.p. in the first few years of the policy implementation; the drop off in bonus claims after year 2 corresponds to the first kink point in the depreciation schedule for Intelligent Location in Table 2. However, these tax write-offs do not translate into any noticeable employment, construction, or other investment responses. We note that the confidence intervals are quite wide, as we lose a lot of statistical power by restricting to observations with $Treatment^{T}_{j,k,t} = 1$.

The results of this subsection suggest that while some firms in Technopolis areas may have made bonus claims under the Intelligent Location policy, the second policy implementation had no additional direct effects on firm hiring and investment. This is perhaps unsurprising given that Intelligent Policy offered the same bonus claims against physical capital investment, but unlike

[38] Goldsmith-Pinkham, Hull, & Kolesár (2021) also consider multiple treatment regressions. They derive efficient estimators for separating treatment effects under the assumption of conditional independence (i.e. under a set of controls), while the de Chaisemartin & D'Haultfœuille (2021) approach relies on the parallel trends assumption. Additionally, the unbiasedness of the estimator requires no anticipation and a balanced panel of firms within the estimation sample. The latter condition is required in our context because we are estimating a "fuzzy" DD, where policy eligibility criteria are set at the city × industry level, but locations are specific to the firm. We confirm that leading the $\beta_{2,t} \to \beta_{2,t+1}$ by one year – as we did with the *BJS* estimator – and restricting to a balanced panel for each outcome does not materially change our results.

FIGURE 6. Dynamic Firm Responses to Intelligent Location Eligibility



Notes: Each panel shows the dynamic response to Intelligent Location eligibility, conditional on already being treated by Technopolis, of an outcome of interest estimated via the staggered DD model in equation (5.8) using the estimator proposed by de Chaisemartin & D'Haultfœuille (2021). With the exception of the bonus depreciation dummy and employment, each variable is deflated by the firm's book assets in 1975 before our estimation sample start date. Firm employment is scaled by its value in 1975. We bin the dummies at the end of the effect window for $t = -4$ and $t = 8$. All dynamic effects are relative to one year before a firm becomes eligible for Intelligent Location. The bars show 95% confidence intervals obtained from standard errors clustered at the firm level, with 1,000 bootstrap iterations. See text for details on the definition of each outcome.

Technopolis, it offered these incentives to firms in industries which rely more on *intangible* capital. Contrasting the two policies reveals the importance of the firm's capital lifespan in determining the success of bonus depreciation initiatives aimed at spurring local economic growth.

5.5 Matched Plant-Parent Firm Analysis

We have so far conducted the analysis at the level of the parent firm. We now turn to the distributional consequences of the investment and employment responses to the Technopolis policy. In this subsection we match the listed firms in the DBJ database to their manufacturing plants in the COM data and address whether the cash flows extracted under Technopolis actually arrived at economically peripheral areas as policymakers intended.

We lack credible within-firm plant identifiers that would allow us to track plants between the 1980 manufacturing facilities reported in the firm's *yuhō* and the manufacturing plants surveyed in COM. However, we know the location of each plant up to the municipality and its 4-digit industry code, and so we can sort plants within the firm on the basis of Technopolis eligibility. Much like our firm-level empirical strategy in Section 4, we set the treatment status of plant i attached to firm j in industry k at time t, $Treatment_{i,j,k,t}$, equal to one if all three of the following criteria are met:

(i) **Plant i level.** The plant is located in an eligible Technopolis municipality.

(ii) **Industry k level.** The firm is operating in one of the eligible 4-digit JSIC industry codes.

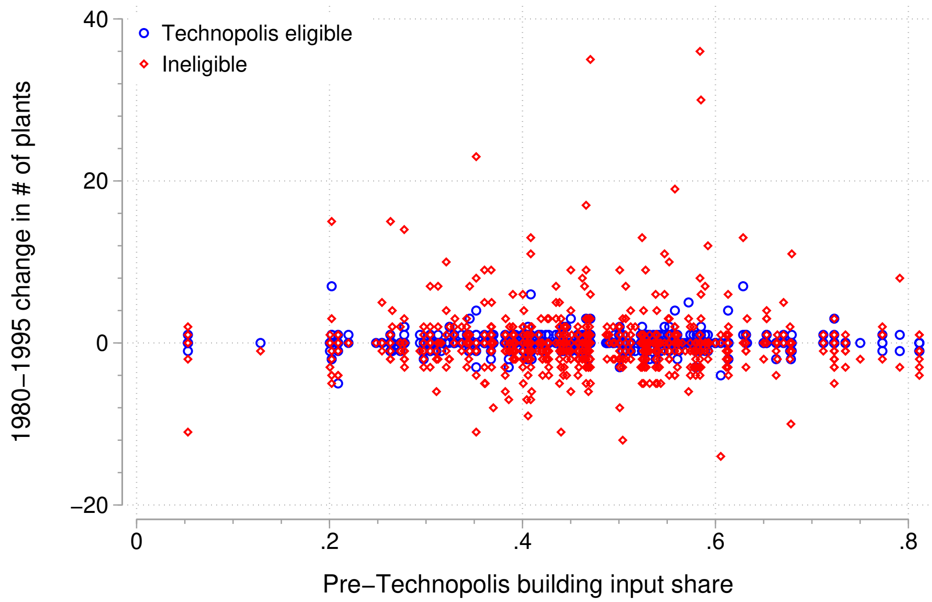
(iii) **Timing t.** If the plant fulfills the above two criteria, then we set $Treatment_{i,j,k,t}$ equal to one for year t equal to or greater than the first eligibility year for the municipality-industry pair.

Under this approach, we find that roughly 13% of the plant-year observations in our matched sample covering 1980 and 1986–2000 are located in a Technopolis eligible area.[39] The number of manufacturing plants in our sample grows from 3,470 in 1980 (from the *yuhō*) to 5,639 in 2000, and peaks at 6,339 plants surveyed in 1997.

We use the building input share ω_{build} constructed in Section 5.3 to sort parent firms based on the attractiveness of the tax incentives offered by Technopolis. As already shown in Table 7, the responses we document in our staggered DD models are driven by firms with a larger share of long-lived assets in production. Hence, we should expect to see a positive gradient between employment growth and investment with respect to ω_{build}. The question is whether this gradient is larger for Technopolis eligible areas. If the gradient is larger for ineligble areas this would indicate that the cash flows firms are extracting from their eligible investments are being used to finance investments in areas not targeted by policymakers.

[39] Under a more stringent definition of $Treatment_{i,j,k,t}$ where in step (ii) we consider the plant treated at the industry level based on the 4-digit industry code attached to the plant rather than the parent firm, we find only 3.4% of plants in the COM sample are eligible. Since the depreciation claims are made at the level of the parent firm, we view it more appropriate to assign the industry eligibility status at the firm level.

FIGURE 7. 1980-1995 Growth in Number of Plants by Technopolis Eligibility



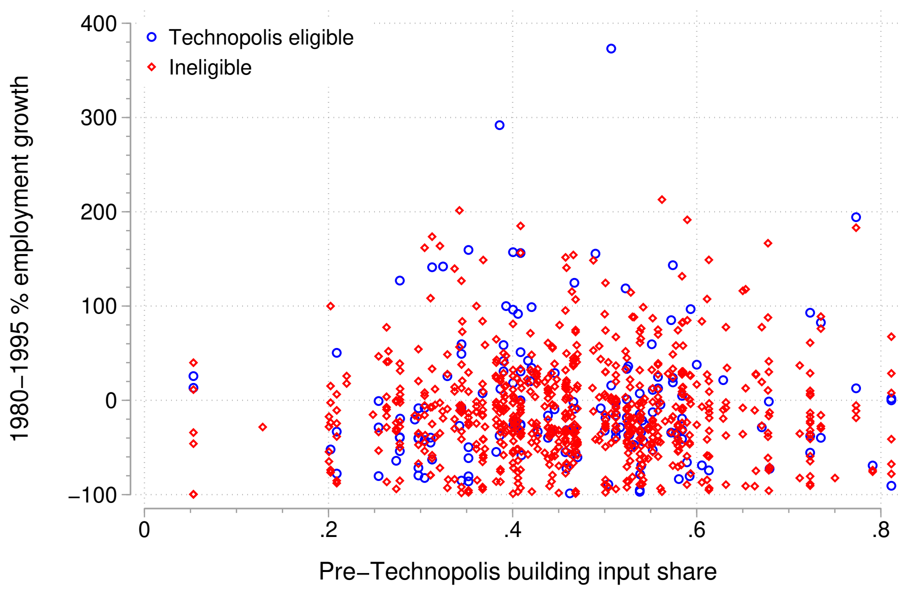
Notes: Each point on the graph corresponds to a DBJ firm matched to the set of manufacturing plants it reported in the COM survey in 1995 and the manufacturing plants it reported in its securities filings in 1980. Points in red represent the 1980–1995 change in the number of plants located in a city not eligible for Technopolis. Points in blue represent the same statistic except computed over plants within the firm's network which are located in cities eligible for Technopolis. Therefore the same firm can appear twice on the plot. The x-axis variable is the firm-level building input share ω_{build} computed via the methods outlined in Section 5.3.

Figure 7 and Figure 8 provide visual evidence in favor of the narrative that ineligible areas captured much of the investment intended for plants in eligible areas. Figure 7 separately computes the change in the total number of eligible (blue) and ineligible plants (red) for each firm and plots these changes in plants against ω_{build}, which can vary between 0 and 1. In cases where a firm has both eligible and ineligible plants, then it will appear twice on the plot. Figure 8 conducts the same exercise except the y-axis is the total employment growth rate (Panel A) or the real book land asset growth rate across all plants in each bucket. To compute real book land asset growth, we deflate the book value of land reported by each plant by the city-level repeat appraisal index for CRE properties in that year compiled by LaPoint (2021). Technopolis overlapped with a dramatic rise in land values, especially commercial land in the CBD, so deflating by the local price index helps isolate the real investment response from the mechanical effects of spatial differences in land price inflation. We compute growth over 1980 and 1995 to allow all Technopolis locations to become eligible – recall the last one was enacted in 1989 – and to allow construction projects begun during the initial Technopolis period to be completed.[40]

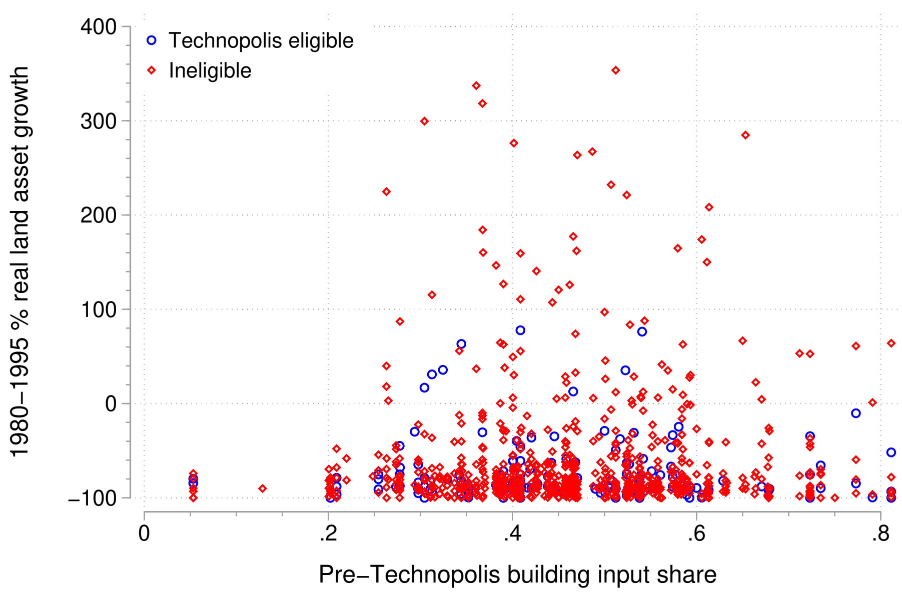
[40]Based on construction itemizations hand-collected from the 1980 *yuhō* corresponding to our sample of DBJ firms, the average projected time to completion for construction projects is 1.5 years, with a maximum duration of 5 years.

FIGURE 8. Employment Growth and Land Acquisitions by ω_{build}

A. 1980-1995 employment growth



B. 1980-1995 real land asset growth



Notes: In both panels, each point on the graph corresponds to a DBJ firm matched to the set of manufacturing plants it reported in the COM survey in 1995 and the manufacturing plants it reported in its securities filings in 1980. Points in red represent the 1980–1995 percentage growth rate in either the number of employees (Panel A) or the real acquisition value of land (Panel B) summing across all plants within the same firm located in a city not eligible for Technopolis. Points in blue represent the same statistics except computed over plants within the firm's network which are located in cities eligible for Technopolis. Therefore the same firm can appear twice on the plot. The x-axis variable is the firm-level building input share ω_{build} computed via the methods outlined in Section 5.3. To obtain real land values, we use the set of commercial real estate price indices constructed in LaPoint (2021). We winsorize growth rates at the 99th percentile.

At the extensive margin of investment in Figure 7 we observe that there is a negligible, positive gradient (slope = 0.119) in the change in the number of plants and ω_{build} for eligible areas, and a negligible but slightly positive gradient for ineligible areas (slope = 0.004). The lack of any discernible relationship between new plant creation and the desirability of bonus claims in both types of areas suggests the bulk of the construction response we document in Section 4 comes from expansions of existing plants in Technopolis areas. In contrast, when we examine employment and real land asset growth in Figure 8, there is a clear divergence between eligible and ineligible areas. For employment growth rates the gradient is 1.918 in eligible areas, and 9.056 in ineligible areas; for real land value growth rates the gradient is −8.560 in eligible areas, but the gradient flips sign to 3.584 in ineligible areas.

This evidence points to much of the gains in firm-level hiring and investment we documented in our main results in Section 5.2 arising from firms allocating resources to ineligible sites.[41] Taken together, it appears our relatively large listed firms expanded existing plants in Technopolis eligible areas to capture the immediate cash flow benefits of bonus depreciation, and then funneled the resources to support other pre-existing plants in ineligible areas. Hence, while the place-based financial incentives offered by Technopolis promoted irreversible investment in areas outside the major metros, it is unclear whether these investments were to the direct benefit of local residents.

6 Fiscal Cost Calculations

In this section, we assess the cost-effectiveness of Technopolis by converting the difference-in-differences estimates of Section 5 to a cost-per-job measure. Following Garrett, Ohrn, & Suárez Serrato (2020), the fiscal cost per dollar of CAPX is the present discounted value of corporate income tax revenue forgone from offering bonus depreciation during the policy regime. In our setting, that implies the accounting identity:

$$\text{Fiscal cost} = \sum_{t=1984}^{1995} \frac{\tau_t}{(1+r)^t} \times \left(D_t^{bonus} - D_t^{normal}\right) \times \text{Take-up}_t \tag{6.1}$$

where we compute the fiscal cost from 1984 through 1995, the final year that firms could claim bonus depreciation through investing in the first wave of Technopolis clusters. We feed in the historical corporate income tax rates τ_t and assume at baseline a constant real discount rate of 7% to render our estimates directly comparable to those in the literature on accelerated depreciation.[42] Corporate income tax rates vary between 43.3% and 37.5% during the policy period, and for a given

[41] While we observe other variables at the plant-level in COM such as acquisition of buildings and machines, at the moment we have no way to link these measures to the information reported at the plant level in the securities filings of our DBJ firms. In future work, we plan to expand the set of outcomes in this matched setting and run plant-level regressions by backfilling plant identifiers to before the Technopolis policy.

[42] A real discount rate of 7% turns out to be roughly equal to the average observed daily rate on the 1-year JGB of 6.4% during the first year of the policy.

tax year the rate is the same for all corporations with above \$80,000 in taxable earnings.[43] The gap between D_t^{bonus} and D_t^{normal} represents the difference per dollar of investment in the benefit to firms under the bonus regime relative to under the benchmark accounting methods available in the tax code. Since firms can normally elect to amortize costs via declining balance [DB] or straight-line [SL] depreciation, we can write D_t^{normal} as:

$$D_t^{normal} = \xi \cdot D_t^{DB} + (1 - \xi) \cdot D_t^{SL} \tag{6.2}$$

where ξ is the share of firms who choose declining balance.[44] 93% of firms in our sample use the more accelerated declining balance method for at least some of their investments, and the remaining 7% use a combination of either straight-line or other methods allowed for certain niche asset classes.[45]

The last component of the accounting identity is the take-up rate, or the share of firms which are both classified as a Technopolis eligible 4-digit JSIC and claim bonus depreciation. 41% of corporations claim bonuses at least once during the policy period, with an average take-up rate of 11.3%. It is necessary to scale by eligibility because some bonus claims are allowed outside the Technopolis regime – for example, airline companies purchasing aircraft – and we cannot separate Technopolis bonus claims from other non-Technopolis bonus claims. Putting everything together, we calculate a baseline fiscal cost of 3.3% per dollar of qualifying capital investment from (6.1).

A final step is needed to produce the fiscal cost in dollars. We compute aggregate CAPX among our firms over the policy period by summing up the firm-level changes in the gross book value of physical capital between 1984 and 1995. This results in \$1.55 trillion in corporate CAPX (155.4 trillion JPY), but not all of this investment satisfied the industry and location eligibility criteria for bonuses. We scale total CAPX down by computing the share of eligible investment among manufacturing firms for which we have investment itemized by plant location:

$$\frac{\sum_{t=0}^{T} \sum_i \Delta PPE_{i,t} \times Treatment_{i,k,t}}{\sum_{t=0}^{T} \sum_i \Delta PPE_{i,t}} \tag{6.3}$$

where $Treatment_{i,k,t}$ is equal to one if plant i is located in a Technopolis area and attached to a parent firm in industry k that is one of the treated 4-digit JSICs. The investment eligibility rate implied by (6.3) is 6.1%, resulting in \$94.79 billion in eligible corporate CAPX conducted under Technopolis. The fiscal cost in dollars amounts to \$94.79 billion $\times$ 3.3% = \$3.13 billion.

It is far more straightforward to compute a measure of jobs generated by Technopolis. Our

[43] We obtained the historical corporate income tax rate series from an official Ministry of Finance memo: `https://www.mof.go.jp/tax_policy/summary/corporation/c01.htm`. A lower, flat rate applies to firms with taxable earnings below the \$80,000 (8 million JPY) threshold. None of the publicly listed firms qualifies for the lower rate in any year of our sample.

[44] We describe these accounting methods in detail through several cash flow simulation exercises in Appendix C.

[45] With the exception of bonus claims, we cannot separate depreciation claims by normal accounting method. We only observe the list of methods a firm uses in a given fiscal year.

preferred DD estimate of the employment response from Figure 4 is 5% relative to 1975 firm employment. Scaling up total listed firm employment in 1975 by 5% implies 185,470 corporate jobs created, leading to a cost per job of \$3.13 billion/185,470 $\approx$ \$16,878. If we instead use our pooled OLS estimate (Table 5) of a 7% bump in employment, then 259,658 jobs were created, and the cost per job falls to \$12,055.

How reliable are these cost-per-job estimates? One advantage to using balance sheet data is that we can compute the lost corporate income tax revenues using the observed stream of bonus and non-bonus depreciation claims. This means our measure calculated via (6.1) is an *ex post* fiscal cost, whereas estimates in the literature generally assume an average benefit rate implied by the wedge $D_t^{bonus} - D_t^{normal}$, and then use that benefit rate to scale down aggregate CAPX eligible for the tax break and produce an overall dollar value cost. On the other hand, our access to balance sheets is predicated on a firm being publicly listed, so this measure only recovers the fiscal cost per large corporate job.[46]

The \$17,000 per job number is also an overestimate, because the factor we apply from (6.3) to pare down total CAPX to eligible CAPX is calculated across manufacturing plants, which we know were already more concentrated in areas designated a Technopolis cluster. Hence, our 6.1% scale factor is biased upward by selection. Finally, we emphasize that due to the nature of the DD estimates we use to calibrate the overall employment gains, our estimate does not take into account general equilibrium forces through which hiring might increase. Yet, we find no evidence of trade network or local spillover effects on firm-level employment, suggesting general equilibrium forces play a limited role in our setting.

7 Conclusion

We investigate the effects of spatial bonus depreciation incentives on local investment, hiring, and corporate (re)location decisions using a series of bonus depreciation schemes in 1980s and 1990s Japan that altered the relative cost of capital across locations. Our results highlight the critical role firms' physical capital structure – which consists of both the geographic distribution of corporate resources and the composition of inputs used in production – plays in the targeting vs. retention trade-off within spatially targeted tax incentives. We find that multi-plant firms exercised these tax write-offs to increase their current cash flow by engaging in construction projects at locations within their internal network and investing in complementary non-real estate assets such as machinery. Our estimated effects are economically large. A firm which became eligible to claim bonus depreciation on investments at one of its plant locations increased its outlays for construction by 0.29 standard deviations and increased its non-real estate assets by 0.40 standard deviations.

[46] We are not aware of any extant reports confirming the value of aggregate depreciation claims (including both corporate and non-corporate entities) eligible under Technopolis. Therefore, we cannot perform the simpler calculation of scaling down aggregate depreciation claims by a measure of the average increase in the present value of deductions relative to the identity in (6.1) for D_t^{normal} we can obtain from cash flow simulations.

Much like the U.S. experience with Opportunity Zones enacted in 2017, which grant capital gains tax deferrals in exchange for a five-year investment in distressed neighborhoods, our setting features immediate financial incentives, targeting firms in high-tech manufacturing industries with long-lived capital structures. Another important distinction of the bonus depreciation schedules offered by Japan's Technopolis policy is that they applied to investment in buildings, an exceptionally long-lived asset class which was ineligible for bonus depreciation episodes in the U.S. in 2001 and 2008. We argue local bonus depreciation incentives promote retention of local capital in contexts where eligible firms rely heavily on long-lived assets in their production function, and bonus claims are attractive relative to existing cost amortization methods allowed under the tax code.

At the same time, we uncover mixed evidence that place-based incentives extended to large multi-plant firms can stimulate peripheral labor markets. We find no evidence of positive local spillovers to firms operating in eligible areas but which were ineligible for bonus claims due to their industry classification, or spillovers via indirect policy exposure through inter-regional trade. While firm-level hiring increased by around 7% after 10 years of the new policy regime, this response was apparently driven by firms hiring at sites where physical investment was not eligible for bonus claims. Future work will take our reduced-form estimates of firm responses to local tax incentives and examine the distributional consequences of place-based policy instruments through the lens of a structural model of multi-location firms using long-lived and short-lived capital.

References

Acemoglu, D. & P. Restrepo (2020): "Robots and Jobs: Evidence from U.S. Labor Markets," *Journal of Political Economy*, 128(6): 2188-2244.

Adelino, M., A. Schoar, & F. Severino (2015): "House Prices, Collateral, and Self-Employment," *Journal of Financial Economics*, 117: 288-306.

Arefeva, A., M.A. Davis, A.C. Ghent, & M. Park (2021): "Job Growth from Opportunity Zones" *mimeo*, Wisconsin-Madison.

Austin, B., E. Glaeser, & L. Summers (2018): "Jobs for the Heartland: Place-Based Policies in 21st-Century America, *Brookings Papers on Economic Activity*: 151-232.

Bahaj, S., A. Foulis, & G. Pinter (2020): "Home Values and Firm Behavior," *American Economic Review*, 110(7): 2225-2270.

Bartik, T.J. (2020): "Using Place-Based Jobs Policies to Help Distressed Communities," *Journal of Economic Perspectives*, 34(3): 99-127.

Berger, A.N. & G.F. Udell (1995): "Relationship Lending and Lines of Credit in Small Firm Finance," *The Journal of Business*, 68(3): 351-381.

Bernard, A.B. & T. Okubo (2016): "Product Switching and the Business Cycle," NBER Working Paper, No. 22649.

Borusyak, K., X. Jaravel, & J. Spiess (2021): "Revisiting Event Study Designs: Robust and Efficient Estimation," *mimeo*, LSE.

Busso, M., J. Gregory, & P. Kline (2013): "Assessing the Incidence and Efficiency of a Prominent Place Based Policy," *American Economic Review*, 103(2): 897-947.

Callaway, B. & P.H.C. Sant'Anna (2021): "Difference-in-Differences with Multiple Time Periods," *Journal of Econometrics*, 225(2): 200-230.

de Chaisemartin, C. & X. D'Haultfœuille (2020): "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review*, 110(9): 2964-2996.

de Chaisemartin, C. & X. D'Haultfœuille (2021): "Two-Way Fixed Effects Estimators with Several Treatments," *mimeo*, UC Santa Barbara.

Chaney, T., D. Sraer, & D. Thesmar (2012): "The Collateral Channel: How Real Estate Shocks Affect Corporate Investment," *American Economic Review*, 102(6): 2381-2409.

Chen, J., E.L. Glaeser, & D. Wessel (2019): "The (Non-) Effect of Opportunity Zones on Housing Prices," NBER Working Paper, No. 26587.

Chirinko, R.S., S.M. Fazzari, & A.P. Meyer (1999): "How Responsive is Business Capital Formation to its User Cost?" *Journal of Public Economics*, 74: 53-80.

Cooper, R.W. & J.C. Haltiwanger (2006): "On the Nature of Capital Adjustment Costs," *Review of Economic Studies*, 73(3): 611-633.

Criscuolo, C., R. Martin, H.G. Overman, & J. Van Reenen (2019): "Some Causal Effects of an Industrial Policy," *American Economic Review*, 109(1): 48-85.

Desai, M.A. & A.D. Goolsbee (2004): "Investment, Overhang, and Tax Policy," *Brookings Papers on Economic Activity*, 2: 285-338.

De Simone, L., R. Lester, & A. Raghunandan (2019): "Do Targeted Business Tax Subsidies Achieve Expected Benefits?" *mimeo*, Stanford GSB.

Devereux, M.P., R. Griffith, & H. Simpson (2007): "Firm Location Decisions, Regional Grants and Agglomeration Externalities," *Journal of Public Economics*, 91: 413-435.

Dougal, C., C.A. Parsons, & S. Titman (2015): "Urban Vibrancy and Corporate Growth," *Journal of Finance*, 70(1): 163-210.

Edgerton, J. (2010): "Investment Incentives and Corporate Tax Asymmetries," *Journal of Public Economics*, 94: 936-952.

Fajgelbaum, P.D. E. Morales, J.C. Suárez Serrato, & O. Zidar (2018): "State Taxes and Spatial Misallocation," *Review of Economic Studies*, 86(1): 333-376.

Forslid, R. & T. Okubo (2014): "Spatial Sorting with Heterogeneous Firms and Heterogeneous Sectors," *Regional Science and Urban Economics*, 46: 42-56.

Freedman, M., S. Khanna, & D. Neumark (2021): "The Impacts of Opportunity Zones on Zone Residents," NBER Working Paper, No. 28573.

Ganong, P. & D. Shoag (2017): "Why Has Regional Income Convergence in the U.S. Declined?" *Journal of Urban Economics*, 102: 76-90.

Garrett, D.G., E. Ohrn, & J.C. Suárez Serrato (2020): "Tax Policy and Local Labor Market Behavior," *American Economic Review: Insights*, 2(1): 83-100.

Gaubert, C. (2018): "Firm Sorting and Agglomeration," *American Economic Review*, 108(11): 3117-3153.

Gaubert, C., P.M. Kline, D. Vergara, & D. Yagan (2021): "Trends in U.S. Spatial Inequality: Concentrating Affluence and a Democratization of Poverty," NBER Working Paper, No. 28385.

Giroud, X., S. Lenzu, Q. Maingi, H. Mueller (2021): "Propagation and Amplification of Local Productivity Spillovers," NBER Working Paper, No. 29084.

Giroud, X. & H.M. Mueller (2015): "Capital and Labor Reallocation within Firms," *Journal of Finance*, 70(4): 1767-1804.

Giroud, X. & H.M. Mueller (2019): "Firms' Internal Networks and Local Economic Shocks," *American Economic Review*, 109(10): 3617-3649.

Glaeser, E.L. & J.D. Gottlieb (2008): "The Economics of Place-Making Policies," NBER Working Paper, No. 14373.

Goldsmith-Pinkham, P., P. Hull, & M. Kolesár (2021): "On estimating Multiple Treatment Effects with Regression," *mimeo*, Yale.

Goodman-Bacon, A. (2021): "Difference-in-differences with Variation in Treatment Timing," *Journal of Econometrics*, 225(2): 254-277.

Goolsbee, A. (1998): "Investment Tax Incentives, Prices, and the Supply of Capital Goods," *Quarterly Journal of Economics*, 113(1): 121-148.

Hadlock, C.J. & J.R. Pierce (2010): "New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index," *Review of Financial Studies*, 23(5): 1909-1940.

Hayashi, F. (1990): "Taxes and Corporate Investment in Japanese Manufacturing," in *Productivity Growth in Japan and the United States*, ed. by C. Hulten, Chicago: University of Chicago Press.

Hayashi, F. & T. Inoue (1991): "The Relation between Firm Growth and Q with Multiple Capital Goods: Theory and Evidence from Panel Data on Japanese Firms," *Quarterly Journal of Economics*, 59(3): 731-753.

Holmes, T.J. (2005): "The Location of Sales Offices and the Attraction of Cities," *Journal of Political Economy*, 113(3): 551-581.

Holmes, T.J. (2011): "The Diffusion of Wal-Mart and Economies of Density," *Econometrica*, 79(1): 253-302.

House, C.L. & M.D. Shapiro (2008): "Temporary Investment Tax Incentives: Theory with Evidence from Bonus Depreciation," *American Economic Review*, 98(3): 737-768.

Ito, K. (1995): *Kenshō Nihon no Technopolis*, Tokyo: Nihon Hyōronsha.

Jia, P. (2008): "What Happens When Wal-Mart Comes to Town: An Empirical Analysis of the Discount Retailing Industry," *Econometrica*, 76(6): 1263-1316.

Kennedy, P. & H. Wheeler (2021): "Neighborhood-Level Investment from the U.S. Opportunity Zone Program: Early Evidence," *mimeo*, UC Berkeley.

Kerr, W.R. & S.D. Kominers (2015): "Agglomerative Forces and Cluster Shapes," *Review of Economics and Statistics*, 97(4): 877-899.

Kline, P. & E. Moretti (2014): "Local Economic Development, Agglomeration Economies, and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority," *Quarterly Journal of Economics*, 129: 275-331.

Kondo, K. (2019): "Municipality-level Panel Data and Municipal Mergers in Japan," RIETI Data Management Project, https://www.rieti.go.jp/en/publications/summary/19030013.html.

LaPoint, C. (2021): "You Only Lend Twice: Corporate Borrowing and Land Values in Real Estate Cycles," *mimeo*, Yale.

Lian, C. & Y. Ma (2021): "Anatomy of Corporate Borrowing Constraints," forthcoming, *Quarterly Journal of Economics*.

Ma, S., J. Murfin, & R. Pratt (2021): "Young Firms, Old Capital," forthcoming, *Journal of Financial Economics*.

Maffini, G., J. Xing, & M.P. Devereux (2019): "The Impact of Investment Incentives: Evidence from UK Corporation Tax Returns," *American Economic Journal: Economic Policy*, 11(3): 361-389.

Mast, E. (2020): "Race to the Bottom? Local Tax Break Competition and Business Location," *American Economic Journal: Applied Economics*, 12(1): 288-317.

Ministry of International Trade and Industry (1995): "The Catalogue of Equipment and Facilities Eligible for Bonus Depreciation," MITI Kinki Office.

Neumark, D. & J. Kolko (2010): "Do Enterprise Zones Create Jobs? Evidence from California's Enterprize Zone Program," *Journal of Urban Economics*, 68: 1-19.

Nihon Location Center (1999): *Technopolis, Zunō Ritti Kōsō Suishin no Ayumi.*

Oberfield, E., E. Rossi-Hansberg, P-D. Sarte, & N. Trachter (2020): "Plants in Space," NBER Working Paper, No. 27303.

Ohrn, E. (2019): "The Effect of Tax Incentives on U.S. Manufacturing: Evidence from State Accelerated Depreciation Policies," *Journal of Public Economics*, 180.

Okubo, T. & E. Tomiura (2012): "Industrial Location Policy, Productivity and Heterogeneous Plants: Evidence from Japan," *Regional Science and Urban Economics*, 42: 230-239.

Siegloch, S., N. Wehrhöfer, & T. Etzel (2021): "Direct, Spillover, and Welfare Effects of Regional Firm Subsidies," *CEPR Discussion Paper Series*, No. 16129.

Slattery, C. & O. Zidar (2020): "Evaluating State and Local Business Incentives," *Journal of Economic Perspectives*, 34(2): 90-118.

Stein, J.C. (1997): "Internal Capital Markets and the Competition for Corporate Resources," *Journal of Finance*, 52(1): 111-133.

Sun, L. & S. Abraham (2021): "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects," *Journal of Econometrics*, 225(2): 175-199.

Walsh, C. (2019): "Firm Creation and Local Growth," *mimeo*, Columbia.

Welch, I. (2020): "Ratio of Changes: How Real Estate Shocks Did Not Affect Corporate Investment," *mimeo*, UCLA.

Yagan, D. (2015): "Capital Tax Reform and the Real Economy: The Effects of the 2003 Dividend Tax Cut," *American Economic Review*, 105(12): 3531-3563.

Yoshida, J. (2020): "The Economic Depreciation of Real Estate: Cross-Sectional Variations and their Return," *Pacific-Basin Finance Journal*, 61: 1-29.

Ziv, O. (2019): "The Micro-Geography of Productivity, Density, and Sorting," *mimeo*, Michigan State.

Zwick, E. & J. Mahon (2017): "Tax Policy and Heterogeneous Investment Behavior," *American Economic Review*, 107(1): 217-248.

Online Appendix to

Place-Based Policies and the Geography of Corporate Investment

by Cameron LaPoint (Yale SOM) and Shogo Sakabe (Columbia)

A Eligible Technopolis Industries & Areas

Here we report the lists of industries and areas where firms could claim bonus depreciation incentives under the Technopolis policy. We hand-collected information in the industry tables from the Ministry of International Trade and Industry (1995) depreciation catalogue, and information in the area tables from the Japan Location Center (1999) history of the two policies.

A.1 List of Eligible Technopolis Industries

Broad Sector	Industry Description
Light Manufacturing	Rayon-acetate
	Synthetic fiber
	Cyclic intermediates, synthetic dyes and organic pigments
	Plastic
	Medical material preparations
	Medical product preparations
	Biological preparations
	Natural drugs and Chinese medicines style medicines
	Medical products for animals
	Porcelain electrical supplies
	Ceramic, stone and clay products, n.e.c
	Food processing machinery and equipment
	Woodworking machinery
	Printing, bookbinding and paper converting machinery
Heavy Manufacturing	Carbonaceous electrodes
	Miscellaneous carbon and graphite products
	Miscellaneous primary smelting and refining of non-ferrous metals
	Rolling and drawing of copper and copper alloys
	Rolling of aluminum and aluminum alloys, including drawing and extruding
	Miscellaneous rolling of non-ferrous metals and alloys, including drawing and extruding
	Electric wire and cable, except optical fiber cable
	Non-ferrous metal products, n.e.c.
	Mechanical power transmission equipment, except ball and roller bearings
	Valves and fittings
	Ball and roller bearings
	Foundry equipment
	Machinery for fabrication of plastic and its equipment

	Metal machine tools
	Metalworking machinery and its equipment, except metal machine tools
	Parts and accessories for metal working machines and machine tools, except machinists' precision tools, molds and dyes
	Machinists' precision tools, except powder metallurgy products
	Molds and dyes, parts and accessories for metal products
	Robots
Transportation	Logistics and conveying equipment
	Motor vehicles, including motorcycles
	Motor vehicles parts and accessories
	Aircraft
	Aircraft engines
	Miscellaneous aircraft parts and auxiliary equipment
Electronics	Office machinery and equipment
	Manometers, flow meters and quantity gauges
	Precision measuring machines and instruments
	Analytical instruments
	Testing machines
	Miscellaneous measuring instruments, analytical instruments, testing machines, surveying instruments and physical and chemical instruments
	Medical instruments and apparatus
	Microscopes and telescopes
	Cameras, motion picture equipment and their parts
	Movie machines and their pats
	Optical lenses and prisms
	Electron tubes
	Semiconductor element
	Integrated circuits
	Miscellaneous electronic components
	Generators, motors and other rotating electrical machinery
	Electrical relay switches
	Auxiliary equipment for internal combustion engines
	X-ray equipment
	Miscellaneous electronic equipment
	Electric measuring instruments, except otherwise classified
	Industrial process controlling instruments
	Miscellaneous electrical machinery equipment and supplies
	Communication equipment wired
	Communication equipment wireless
	Video equipment
	Computer, except personal computer

Notes: The table lists the 4-digit JSIC industries eligible to claim bonus depreciation under the Technopolis policy, obtained from Ministry of International Trade and Industry (1995). We crosswalk historical JSICs to the modern classification system. See Section 2 for more details on the policy, including the bonus rate schedule.

A.2 List of Eligible Technopolis Areas

The table below reports the list of Technopolis-eligible areas, which include 26 named "Technopolises," each of which forms a cluster around a large regional city. In total, there are 141 municipalities (according to modern Census city codes) included within these 26 sites. For conciseness, we list each Technopolis site, the regional hub it corresponds to, the number of cities (*shi*) and towns (*machi* or *mura*) included in the catchment area, and the policy rollout date.

Technopolis Name	Policy Date	Regional City	# Cities	# Towns	# Unique City Codes
Central Hiroshima	3/24/1984	Kure	3	2	3
Hamamatsu	3/24/1984	Hamamatsu	3	3	2
Kumamoto	3/24/1984	Kumamoto	2	11	9
Miyazaki	3/24/1984	Miyazaki	1	6	3
Northeastern Kyushu	3/24/1984	Oita	6	15	8
Shinanogawa	3/24/1984	Nagaoka	8	7	9
Southern Kyushu	3/24/1984	Kagoshima	2	12	4
Toyama	3/24/1984	Toyama	2	4	3
Ube	3/24/1984	Ube	4	4	4
Akita	5/21/1984	Akita	1	2	1
Utsunomiya	5/21/1984	Utsunomiya	2	2	4
Hakodate	7/14/1984	Hakodate	1	3	3
Yoshino Plateau	8/3/1984	Okayama	3	5	4
Kurume-Tosu	9/17/1984	Kurume	2	5	4
Nagasaki	3/12/1985	Sasebo	3	3	6
Aomori	8/14/1985	Aomori	5	2	6
Western Suma	9/18/1985	Himeji	4	9	8
Kagawa	12/6/1985	Takamatsu	5	7	8
Koriyama	12/3/1986	Koriyama	2	4	6
Northern Sendai	12/3/1986	Sendai	1	4	5
Kitakami River Basin	9/24/1987	Morioka	5	1	5
Yamagata	9/24/1987	Yamagata	5	1	6
Asama	12/25/1987	Nagano	4	7	8
Kofu	2/12/1988	Kofu	2	19	10
Ehime	4/26/1988	Matsuyama	6	6	7
Central Hokkaido	2/14/1989	Sapporo	4	1	5
Total	–	–	86	145	141

Notes: Technopolis sites are listed in chronological order based on policy implementation date. In some cases (e.g. the "Northeastern Kyushu" Technopolis) we translated portmanteaus to reflect the region of Japan where the catchment area is located. The number of cities and towns refers to the number of historical jurisdictions in those two official area categories. In the final column, the number of unique Census city codes is weakly less than the sum of the number of distinct cities and towns due to municipal mergers. We impose modern municipality boundaries using the historical city code crosswalk available through RIETI (Kondo 2019). Policy dates obtained from Ministry of International Trade and Industry (1995). Eligible sites obtained from Japan Location Center (1999).

B Eligible Intelligent Location Industries & Areas

Here we report the lists of industries and areas where firms could claim bonus depreciation incentives under the Intelligent Location policy. We hand-collected information in the industry tables from the Ministry of International Trade and Industry (1995) depreciation catalogue, and information in the area tables from the Japan Location Center (1999) history of the two policies.

B.1 List of Eligible Intelligent Location Industries & Assets

In contrast to Technopolis, which explicitly listed 4-digit JSICs eligible for bonus depreciation incentives, the Intelligent Location policy instead targeted four broad descriptions of activities that would render firms eligible. Each of these descriptions is attached to a set of "targeted assets," which we map to 4-digit JSICs.

Broad Industry Description	**2-digit Category**	**4-digit Category**
Industrial Machinery & Equipment Leasing	Goods Rental & Leasing	Leasing management
		General goods leasing
		Industrial equipment rental
		Office machinery rental
		Automobile rental
		Sports and hobby goods rental
		Audio and visual recording rental
		Theatrical goods rental
Machinery Repair	Machine Repair Services	Repair management
		Machine repair shops, except electrical appliances
		Electrical machine and appliance repair
Software	Information Services	Information management
		Computer programming and software services
		Data processing
		Information services, except marketing or surveys
		Miscellaneous data processing
Information Processing/Provision	Communication Electronics	Equipment management
		Communication equipment

		Image and audio equipment
		Electronic data processing machines
Industrial Design	Technical Services	Mechanical design services
Industrial Installation	Equipment Installation Work	Installation management
		Electric work
		Telecommunication and signal work
		Piping work, except water-well drilling
		Machine and equipment installation
		Miscellaneous equipment installation
Natural Sciences R&D	Scientific Research Institutes	R&D management
		Research institutes for natural sciences
Chemical Research Instruments		Measuring instruments, analytical instruments, testing machines, chemical instruments
		Medical instruments
		Optical instruments
	Equipment wholesale trade	Miscellaneous machinery and equipment

Notes: The table lists the 4-digit JSIC industries eligible to claim bonus depreciation under the Technopolis policy, obtained from Ministry of International Trade and Industry (1995). We crosswalk historical JSICs to the modern classification system. Unlike Technopolis, the Intelligent Location policy does not list specific 4-digit industry codes which are eligible. Rather, it offers descriptions of eligible production activities which we map to 4-digit JSICs. See Section 2 for more details on the policy, including the bonus rate schedule.

B.2 List of Eligible Intelligent Location Areas

The table below reports the list of Intelligent Location-eligible areas, which include 26 named "Intelligent Cities." In total, there are 319 municipalities (according to modern Census city codes) included within these 26 sites. Of these, 75 municipalities were previously eligible for bonus incentives under Technopolis. We list each policy site, the regional hub it corresponds to, the number of cities (*shi*) and towns (*machi* or *mura*) included in the catchment area, and the enactment date.

Intelligent Location	**Policy Date**	**Regional City**	**# Cities**	**# Towns**	**# Unique City Codes**
Hachinohe	3/15/1989	Hachinohe	2	8	10
Toyama	3/15/1989	Toyama	6	7	13
Hamamatsu	3/15/1989	Hamamatsu	1	0	1
Tokushima	3/15/1989	Tokushima	3	13	16
Ishikawa	2/23/1990	Kanazawa	3	9	12
Kagoshima	2/23/1990	Kagoshima	2	2	4
Kofu	2/23/1990	Kofu	1	12	13
Okayama	2/23/1990	Okayama	4	2	6
Central Hiroshima	3/15/1990	Kure	3	6	9
Kita-Kyushu	3/15/1990	Kita-Kyushu	7	12	19
Tottori	3/15/1990	Tottori	1	10	11
Wakayama	3/15/1990	Wakayama	3	13	16
Mito-Hitachi	8/28/1990	Mito	4	5	9
Oita	8/28/1990	Oita	5	6	11
Okinawa	8/28/1990	Naha	7	15	22
Koriyama	3/29/1991	Koriyama	2	4	6
Asahikawa	9/20/1991	Asahikawa	8	17	25
Gunma	9/20/1991	Maebashi	5	9	14
Yamagata	4/10/1992	Yamagata	9	4	13
Kagawa	6/17/1992	Takamatsu	5	9	14
Nagasaki	6/17/1992	Sasebo	3	7	10
Yamaguchi	6/17/1992	Ube	3	3	6
Gifu	11/26/1992	Gifu	6	15	21
Miyazaki	1/31/1994	Miyazaki	3	12	15
Morioka	1/31/1994	Morioka	3	8	11
Utsunomiya	1/31/1994	Utsunomiya	0	12	12
Total	–	–	99	220	319

Notes: Intelligent Location sites are listed in chronological order based on policy implementation date. The number of cities and towns refers to the number of historical jurisdictions in those two official area categories. Unlike Technopolis, the regional hub that lends its name to the industry cluster may not actually be treated itself (e.g. firms in the historical jurisdiction of Hachinohe are not eligible). In the final column, the number of unique Census city codes is equal to the sum of distinct cities and towns after accounting for municipal mergers. We impose modern municipality boundaries using the historical city code crosswalk available through RIETI (Kondo 2019). Policy dates obtained from Ministry of International Trade and Industry (1995). Eligible sites obtained from Japan Location Center (1999).

C Depreciation Accounting Methods

In this appendix we provide additional context on the depreciation accounting methods allowed under the corporate income tax code and present a detailed example of tax benefits a typical qualifying investment in tangible assets would receive in our setting. When a firm is incorporated, it can decide whether to change its depreciation accounting from the default declining balance method to straight-line accounting. If the firm does not specify an accounting method, any depreciation claims made within the tax year must use the declining balance method. In only 7% of firm-years, firms use a combination of declining balance and straight-line methods. This combination is dictated by input composition and changes to the tax code which require the use of straight-line amortization for certain very long-lived assets (e.g. an industrial storage freezer).[47]

Declining balance is an accelerated depreciation method which results in larger tax write-offs early on in the lifespan of an investment, in exchange for lower tax write-offs later; in that sense, declining balance operates similarly to bonus depreciation but is not as generous in terms of the initial rate. Firms in certain industries can claim bonus depreciation in normal times towards particularly large inputs such as aircraft – a feature which is present in the U.S. tax code as well. Still, 80% of firms rely exclusively on declining balance accounting. As we will show in the example below, the prevalence of declining balance accounting is due to the fact that for most investments it strictly dominates linear cost accounting from a PDV perspective.

These standard accounting methods can be mathematically summarized as follows. Let θ_t denote the depreciation rate in year t of the asset's lifespan. For straight-line (linear) depreciation, this rate is simply equal to $\theta_t = 1/x, \forall t$, where x is the lifespan of the asset. For declining balance, the formula is given recursively by:

$$P_t = P_0 - \sum_{k=1}^{t} \theta_{t-k} \cdot P_{t-k}, \qquad \text{given } \theta_0 \tag{C.1}$$

where P_t refers to the cost basis, and P_0 is the initial cost basis. For all methods, the initial cost basis is set to 90% of the actual investment cost, which corresponds to the concept of a 10% "salvage value" in the U.S.[48] For declining balance, the tax authority calibrates θ_0 such that at $t = x$ only the salvage value remains undepreciated.[49] Across all methods, when $x = 1$, such as with certain kinds of goods inventories, the entire cost can be deducted in the investment year, and there is (mechanically) no difference in rates across methods because $\theta_0 = 1$.

Depreciation rates θ and lifespan x allowed under each method are dictated by the National Tax Agency in Japan. Historically, the rates differed not just by the asset class (e.g. real estate) but by a combination of industry of the taxable parent firm and the use of the asset (e.g. a concrete

[47] For instance, as of the 2017 tax year, building improvements and structures can no longer be deducted using the declining balance approach.

[48] In the U.S. tax code declining balance is defined in terms of a multiple of the straight-line depreciation rate (e.g. "100% or 200% Modified Accelerated Cost Recovery System" [MACRS] in IRS Publication 946). In practice, the rates in our setting are close to the rates obtained under a 200% MACRS rule in the U.S. See Zwick & Mahon (2017) for an example of the 200% declining balance method with bonuses in the U.S.

[49] Importantly, these cost accounting relationships hold even if for some reason a firm does not claim depreciation in a given year. This can happen if a firm is particularly aggressive in its claiming behavior and reaches the limit (with carryovers) in a given filing year.

office building used as an administrative site for a manufacturing company).[50] This schedule is more detailed than tax codes in the U.S., where assets are lumped together into large categories of lifespans, ranging from 3 years for tractors and livestock to 39 years for commercial use properties. Yet, internationally, tax codes share common principles with respect to how lifespans are set, with buildings and industrial machines being among the longest-lived, and office fixtures being among the shortest-lived assets.

Adding bonus depreciation to this system results in the following overall depreciation rates:

$$\theta_t = \begin{cases} \theta^{bonus} + (1 - \theta^{bonus}) \cdot \theta_t^{normal} & \text{if } t = 0 \\ (1 - \theta^{bonus}) \cdot \theta_t^{normal} & \text{if } 0 < t \leq x \end{cases} \tag{C.2}$$

where θ^{bonus} is the bonus depreciation rate (e.g. maximum of 30% for Technopolis), and θ^{normal} refers to the allowed rate under the normal accounting method chosen by firms. Both rates will vary over time depending on tax reforms, and across firms depending on their election of normal depreciation method, their location decisions, and whether they operate in an eligible industry.

The corporate income tax (CIT) bill for income I, asset cost basis P, and depreciation rate θ is:

$$\tau^{CIT} \cdot (I - \theta \cdot P) \tag{C.3}$$

Combining (C.2) and (C.3) the immediate cash flow benefit of Technopolis shows up clearly as:

$$\tau^{CIT} \cdot P_{i,0} \times \left(\theta_{i,c}^{bonus} + (1 - \theta_{i,c}^{bonus}) \cdot \theta_0^{normal}\right) \tag{C.4}$$

where we write $\theta_{i,c}^{bonus}$ to emphasize that bonus rates depend on the location c of the investment and whether the capital good is real estate or non-real estate. National corporate income tax rates can take one of two values: a standard rate for firms earning above 8 million JPY (or roughly 80,000 USD in taxable earnings), or a lower rate for small firms below this earnings threshold. During our sample period, national corporate income tax rates varied between $28\% - 31\%$ for small firms, and $40\% - 43.3\%$ for large firms.[51]

To further illustrate, we now return to the example referenced in Section 2.1 of the main text, which is typical of the corporate investment responses to Technopolis we observe in the data. Suppose a firm invests \$1 million in construction of a new site in a Technopolis area, plus \$1 million in computers to be installed at the new plant when it is finished in 2 years. For reference, the average duration of construction projects in our dataset is 15 months (median of 11 months). The firm faces a corporate income tax rate of $\tau^{CIT} = 40\%$, and can claim the Technopolis bonus rates of $\theta^{bonus} = 30\%$ against the cost of the PCs and and $\theta^{bonus} = 15\%$ against the new building upon its completion.[52] Assume the lifespan of the PCs is four years, while the lifespan of the new office building is 65 years.

[50] A major overhaul of Japan's depreciation schedule in 2008 reduced complexity by stipulating rates that depend only on industrial sector and asset type without any dependence on the use.

[51] The effective corporate income tax rate depends on both the national rate and the accumulation of any local enterprise tax rates set in the local jurisdictions where a firm operates. Technopolis bonuses apply only towards national corporate income tax liability, which generates the bulk of the tax bill for our large multi-plant firms.

[52] Construction unrelated to improvements of existing structures is not a depreciable expense. Instead, allowable depreciation claims must occur after the construction is completed and the asset appears on the balance sheet.

Table C.1. Default and Bonus Depreciation Schedules for Short and Long-lived Items

Year	1	2	3	4	5	...	**Total**	**PDV** ($r = 7\%$)
Straight-line (linear)								
Cash flow (PCs)	90	90	90	90	0	...	360	326
Cash flow (CRE)	0	0	5.5	5.5	5.5	...	360	73
Declining balance (default)								
Cash flow (PCs)	175	98.5	55.5	31	0	...	360	341
Cash flow (CRE)	0	0	14	13.5	13	...	360	124.5
Bonus (Technopolis) + default								
Cash flow (PCs)	242.5	69	39	10	0	...	360	349
Cash flow (CRE)	0	0	72	11.5	11	...	360	158

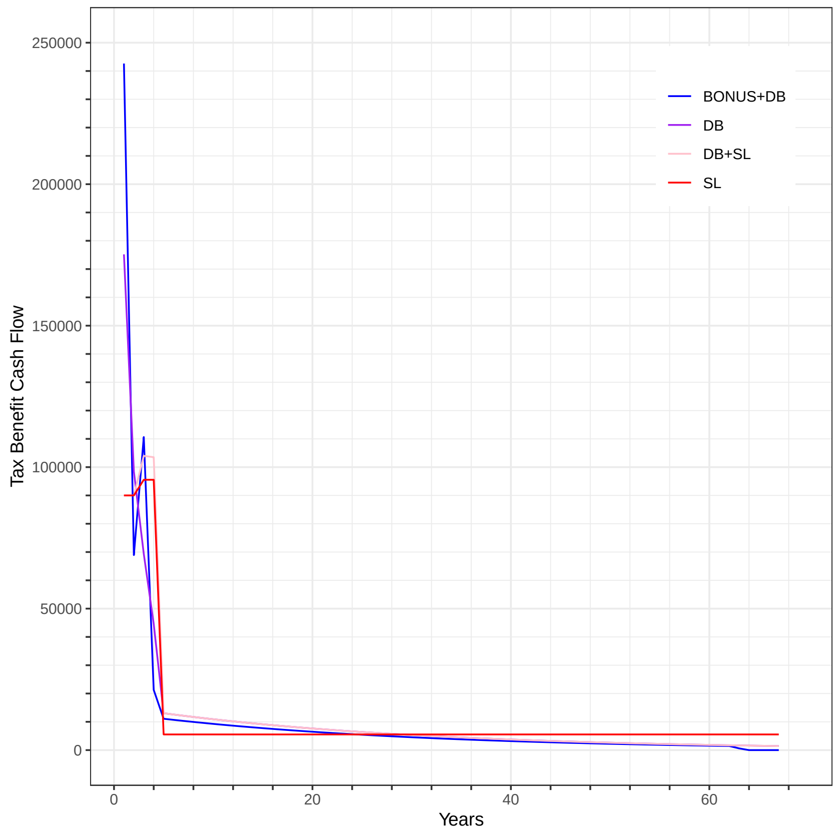
Notes: The table displays year-by-year cash flows from tax benefits of claiming depreciation for the example described in the main text consisting of a \$1 million investment in computers (PCs, lifespan of 4 years) and a \$1 million investment in constructing a new office building (CRE, lifespan of 65 years + 2 year construction horizon). Cash flows in thousands. In normal times, firms have the option of choosing between straight-line (linear) and declining balance (the default) accounting methods. See text for precise formulas underlying these cost amortization schedules. We assume $\tau^{CIT} = 40\%$, $\theta^{bonus} = 30\%$ for PCs and $\theta^{bonus} = 15\%$ for CRE, and for the PDV calculations a 7% annual real discount rate to match the analogous exercise conducted in Zwick & Mahon 2017 for the U.S. To make things simple, we assume the assets are deployed in the first month of the tax year (April), so there is no pro-rating by months within a tax year. The initial basis $P_{i,0}$ is set to 90% of acquisition cost as in the tax code. We sourced the historical declining balance rates from the official depreciation catalogue (MITI 1995). See National Tax Agency, Publication No. 12013 for an overview of the depreciation system in Japan: https://www.nta.go.jp/english/taxes/individual/12013.htm

Table C.1 summarizes the stream of tax benefit flows for these parameters under the most common accounting methods. While all three methods result in the same amount of total deductions (\$720,000 = 40% × [\$2 million outlay − 10% salvage value]), the PDV implications are starkly different: \$507,000 with bonuses vs. \$465,500 under declining balance, and \$399,000 under linear accounting. The shifting of cash flows to the very first few years of the capital life-cycle can be seen in Figure C.1, where we plot the full sequence of cash flows for four methods over the full 67-year investment horizon (65 years of CRE + 2-year construction period), including the three methods in Table C.1 and a hypothetical fourth method ("DB + SL") in which we assume the firm uses linear depreciation for the computers, but declining balance for the buildings.[53]

Finally, in Figure C.2 we consider a generalization of the simple two-asset example in which we project how the PDV of the overall tax benefit of bonuses – benchmarked to the outside option without bonuses – varies with the key accounting parameters: the real discount rate, the cost share of the long-lived asset, and the lifespan of the long-lived asset (holding fixed the lifespan of the other asset). The return to bonus claims, or the CAPX subsidy rate, is concave in the interest rate and asset lifespan, since the incremental gains are smaller as discounting becomes a stronger force. Crucially, the return to bonuses is linear in the *share* of the long-lived asset, but invariant to the dollar amount of the total initial investment, conditional on this share. This simple

[53] We assume all assets are deployed (or construction begins) in April of year 1, so there is no pro-rating of depreciation claims across tax years. Japan does not have the half-year convention as in the U.S. tax code. Hence, if the construction horizon is h, the first year when claims can be made against the newly made asset is $t = h + 1$.

FIGURE C.1. Tax Benefits over the Lifespan of a Typical Investment

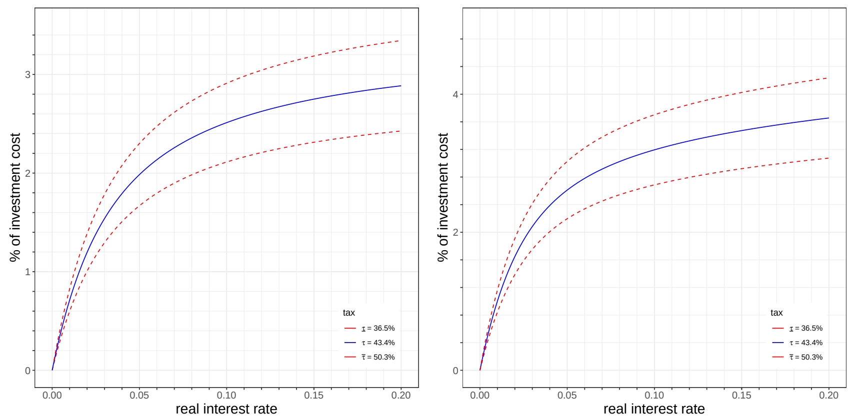


Notes: The figure plots undiscounted tax benefit cash flows over the lifespan of the investment strategy described in the text. We consider four accounting methods: "BONUS + DB" refers to a firm which claims Technopolis bonuses at the maximum possible rate and uses declining balance as it outside option, "DB" refers to declining balance without bonuses, "DB + SL" refers to declining balance claimed against the CRE investment, but straight-line claimed against the PCs, and "SL" refers to linear depreciation against both asset types. By law, under bonus depreciation the total deductions over the asset's lifespan can never exceed the total deductions claimed under the alternative method without the bonus. This truncates the "BONUS + DB" series at $0 in the final years of the lifespan.

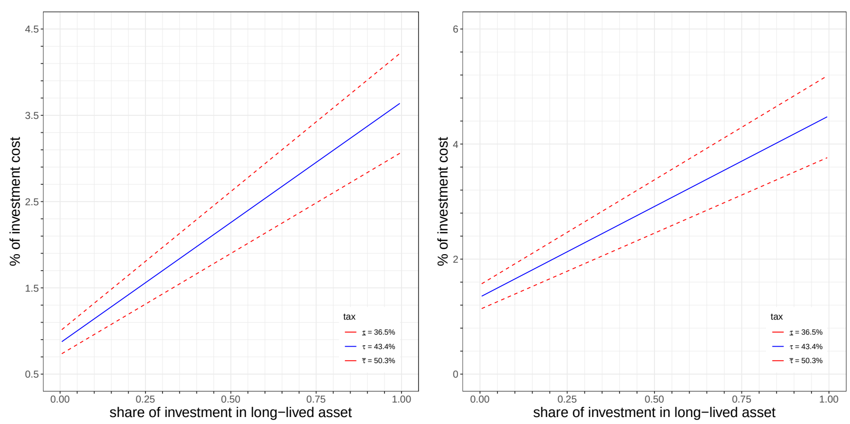
accounting result underlines our use of the production input share of buildings as a measure of firm treatment intensity in Section 5. At the extreme, a firm investing only in a new building but no computers receives a 4% subsidy (Panel B). Panel C shows that if we applied the 39-year tax lifespan of commercial buildings in the U.S. to the Japanese tax code, the construction subsidy under Technopolis would have been between 2% to 3%.

FIGURE C.2. Simulated Tax Benefit PDVs as a Percentage of Investment Cost

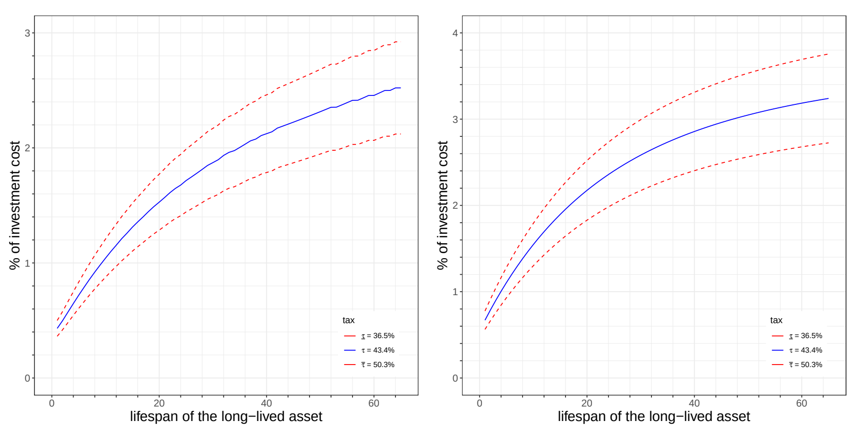
A. Varying the real interest rate



B. Varying the cost share of the long-lived asset



C. Varying the lifespan of the long-lived asset



Notes: Panels in the left-hand column compute the PDV of the total tax benefit flows from bonuses as a percentage of the initial investment cost (i.e. the subsidy rate) benchmarked to declining balance without bonuses; the right-hand column does the same but benchmarked to straight-line depreciation as the normal option. Because θ_0 for the declining balance method is rounded to the third decimal place in the tax code, the relationship between lifespan and returns in the bottom left-hand panel is not strictly monotonic. In each panel, we plot the returns with "confidence intervals" which reflect the range of minimum and maximum effective tax rates (incorporating local and national income tax rates) during our sample period.

D Details on Capital Input Share Calculations

In this appendix we offer some additional details on the perpetual inventory approach and nearest-neighbor matching algorithm outlined in Section 5.3 of the main text. Although a more detailed treatment of the perpetual inventory approach applied to the DBJ data can be found in LaPoint (2021), we emphasize aspects of the procedure that are specific to this paper.

The basic idea behind this approach is that the input shares for each profit-maximizing firm are a function of the user costs, since the marginal rate of substitution in the capital aggregate between any two inputs will be equal to the ratio of the user costs. The key component to this approach is iterating on the investment law of motion to recover real capital inputs:

$$Pk_{i,t} \cdot k_{i,t+1} = (1 - \delta_i) \cdot Pk_{i,t} k_{i,t} + NOMI_{i,t} \tag{D.1}$$

where nominal investment $NOMI_{i,t}$ is the change in net book value of assets of type i plus accounting depreciation. To start the recursion, we convert assets from book to market value using the wholesale price index for each capital good for non-real estate assets, and using the local commercial property price indices constructed in LaPoint (2021) to inflate book values of the real estate components of PPE (buildings + land). We then set $Pk_{i,t}k_{i,t}$ to this market value in the benchmark year of 1975; we truncate the investment series by setting $NOMI_{i,t}$ equal to the book value of assets i as of the end of the year prior to the benchmark year.

From the FOC of the firm's profit maximization problem, the $k_{i,t}$ in the investment law of motion are functions of the user costs of capital, which are in turn a function of observable parameters:

$$c_{i,t} = \left[1 - (1 - \delta_i) \cdot \mathbb{E}_t\left(\beta^R_{i,t,t+1}\right)\right] \cdot \frac{(1 - z_{i,t}) \cdot Pk_{i,t}}{(1 - \tau_t) \cdot P_t} \tag{D.2}$$

$$\beta^R_{i,t,t+1} = \beta_{t,t+1} \cdot \frac{(1 - z_{i,t+1}) \cdot Pk_{i,t+1}}{(1 - z_{i,t}) \cdot Pk_{i,t}} \tag{D.3}$$

Equation (D.3) refers to the asset-specific real discount factor from t to $t+1$, which is obtained by adjusting the nominal overall discount factor $\beta_{t,t+1}$ for asset-specific inflation (Pk_i) and changes to depreciation allowances for that asset type (z_i). We compute the firm's weighted average cost of capital (WACC) and set $\beta_{t,t+1} = 1/(1 + WACC_t)$. We take $\mathbb{E}_t(\beta^R_{i,t,t+1})$ to be the average value of $\beta^R_{i,t,t+1}$ over the panel.

User costs in equation (D.2) reflect output prices net of the corporate income tax rate (τ_t). The effective corporate income tax rate τ_t reflects the combination of a national income tax rate u_t and a local enterprise tax rate v_t which varies by firm location. Since local enterprise taxes paid in t are deductible from income in $t+1$, the effective corporate income tax rate is

$$\tau_t = \frac{(u_t + v_t)(1 + r_t)}{(1 + r_t + v_t)} \tag{D.4}$$

where r_t is a short-term nominal rate proxied by the 1-year Bank of Japan prime lending rate. Unfortunately, many firms in our sample do not separately report national and local taxes paid. This leads to many missing values for the user cost. The other issue that cuts down the sample of firms for which we can directly compute the input shares in production ω_i described in Section 5.3 is that we do not have an adequate empirical proxy for output price P_t for certain types of firms in the real estate, construction, and transportation, and services sectors. In the end, we can directly back out ω_i for about one-third of our sample of DBJ firms.

To impute the ω_i for the firms which lack all the necessary variables to identify the user costs in (D.2), we use a simple nearest-neighbor matching approach. We create a dummy T_j equal to one if firm j has a directly observed ω_i, and then estimate the following logit model with the dummy as the probabilistic outcome:

$$P\Big(T_j = 1 | X_j\Big) = \frac{\exp\Big(h(X_j\Big)}{1 + \exp\Big(h(X_j)\Big)} \tag{D.5}$$

where we include in the function $h(X_j)$ the following variables: dummies for three broad industrial sectors, total assets, and a quadratic in age. We select this parsimonious set of variables to predict the probability of having non-missing user costs because the missing values arise for firms in particular sub-industries, and for firms which may pay more or less taxes on each of the tax bases depending on their age and balance sheet size. We then take the fitted probability value from (D.5) as the propensity score, and compute for each firm j with missing ω_i the squared difference between its propensity score and the propensity score of all firms with non-missing ω_i. The firm $-j$ that has the smallest squared difference in propensity scores then becomes the donor. We donate all of the ω_i from firm $-j$ to firm j.

Table D.1 displays the log odds ratio from estimating our preferred logit model (column 2) and other variations including more or fewer covariates to perform the nearest-neighbor match. Manufacturing is a persistently positive and significant predictor of a firm reporting all variables needed to back out the capital input shares from iterating on the investment law of motion in (D.1), and there is no relationship between balance sheet size or age and reporting completeness. Although this requires us to drop many firms, we also check whether more sophisticated firms – proxied by their pre-reform use of declining balance depreciation accounting – more productive firms (Q ratio), or firms with more cash flow (EBITDA) keep more detailed records. Of these variables, only EBITDA has any significant correlation on our ability to compute capital input shares, implying that firms with higher initial earnings are more fastidious in their bookkeeping.

Table D.2 tabulates the average and standard deviation for each of the six capital input shares for firms sorted into one of eight industrial sectors, including: light manufacturing, heavy manufacturing, real estate, construction, transportation, electronics, non-transportation services, and agriculture. There are intuitive differences in the capital structure across sectors, which provides a sanity check on our nearest-neighbor matching and perpetual inventory approaches to recovering the input shares. For example, heavy manufacturing firms make the most use of machinery in their production, while electronics firms have the highest input share for tools and precision instruments. Unsurprisingly, the transportation sector has the highest input share for vehicles.

In inspecting the differences in physical capital structure for firms in distinct sectors, we underscore that these capital input shares are based on asset ownership, rather than renting. While a real estate and construction firm may have a lot of properties listed on its portfolio, many of these properties are partially leased from third parties. In additional most of the profits from leasing companies come from rental income and management of properties. In contrast, manufacturing firms are more likely to fully own their facilities, and so the building share is therefore highest for that subset of firms.

Figure D.1 plots the distribution of input shares for each capital type, after applying the nearest-neighbor matching. Dashed red lines indicate the average input share reported in Table

D.1. Buildings account for an outsize share of production inputs for the majority of firms in our sample, with an average share of 0.47. At the same time, for all other capital types there is a sizeable mass of firms which have an input share of approximately zero; 9% of DBJ firms do not use machines and 8% of firms do not use vehicles in their operations. The land share of production is low compared to buildings. This reflects, in part, that the listed firms in our sample are more likely to be located in very urban areas where land is scarce and owned office space takes the form of several floors within a larger high-rise.

Table D.1. Nearest-neighbor Matching Logit Model

	(1)	(2)	(3)	(4)
Assets	−0.022	−0.022	−0.011	−0.012
	(0.033)	(0.033)	(0.033)	(0.035)
Age	−0.001	−0.001	−0.004	0.008
	(0.019)	(0.019)	(0.021)	(0.022)
Age^2	0.000	0.000	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Mfg dummy	0.836***	0.825***	0.826***	0.709***
	(0.170)	(0.190)	(0.200)	(0.207)
Retail dummy		0.047	0.086	0.418
		(0.342)	(0.360)	(0.370)
Services dummy		−0.224	−0.207	−0.991
		(0.490)	(0.544)	(0.642)
DB method dummy			0.461	0.346
			(0.329)	(0.344)
Q ratio				−0.163
				(0.114)
EBITDA				7.715***
				(1.504)
Constant	−2.519***	−2.505***	−2.871***	−3.774***
	(0.526)	(0.536)	(0.664)	(0.721)
N	1,507	1,507	1,360	1,334
Pseudo-R^2	0.025	0.025	0.027	0.079

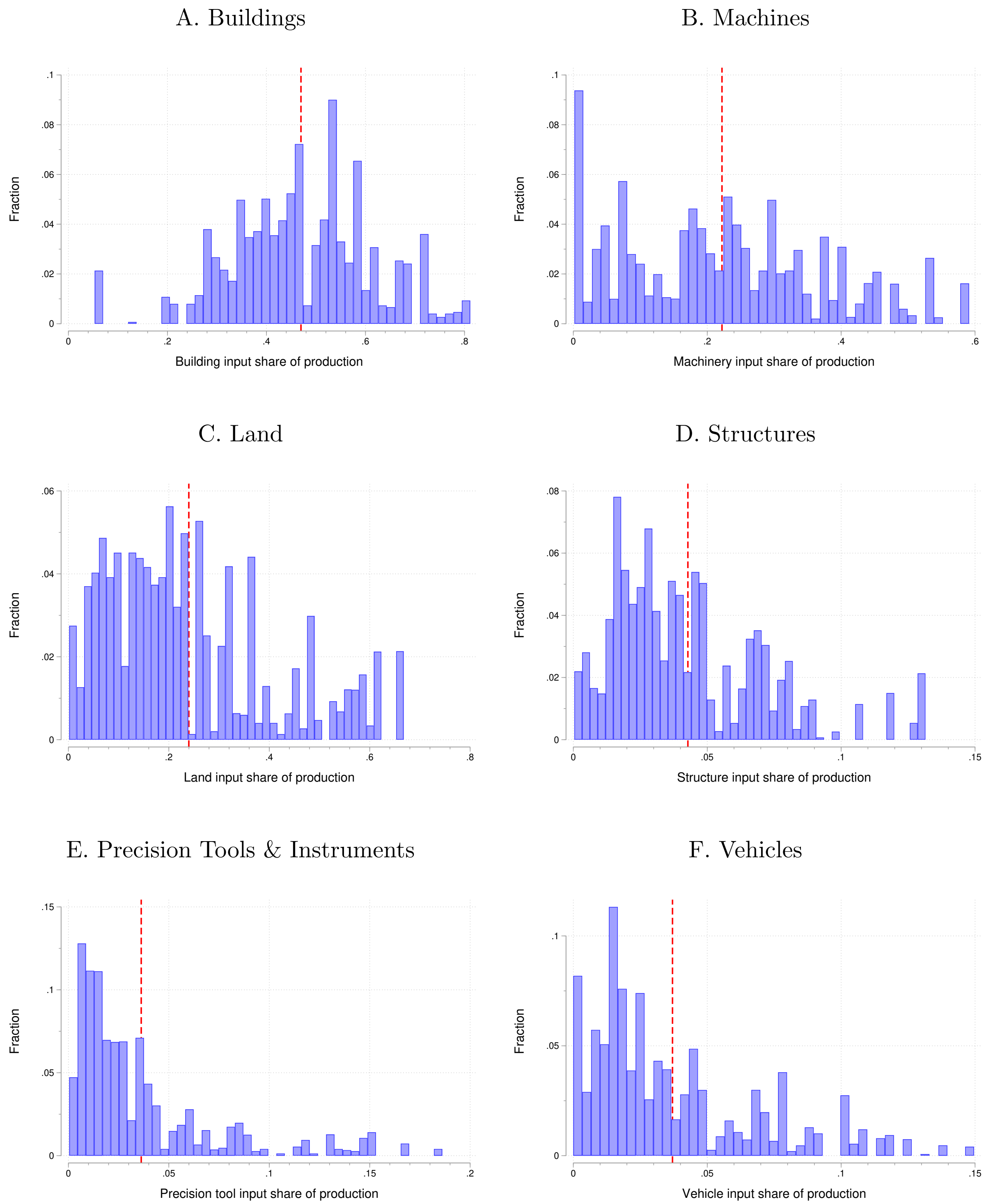
Notes: The table shows the estimated log odds ratios for firm-level characteristics obtained from estimating versions of the logit model in equation (D.5) with the outcome equal to 1 if the firm has all non-missing capital input shares from imposing the perpetual inventory equations. Assets measured as average pre-Technopolis (pre-1984) total assets in millions of yen. Age measured from the Tokyo Stock Exchange listing date. We group firms into coarse manufacturing, retail, and services categories based on their one-digit JSIC. DB method dummy is equal to unity if the firm uses declining balance depreciation accounting methods in the pre-Technopolis period. EBITDA is defined using standard accounting principles. The Q ratio is the ratio of the market value of the firm (total assets + market equity − common equity − deferred tax payments relative to book assets). Both EBITDA and the Q ratio are deflated by total assets in the first year before the sample start date. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table D.2. Capital Input Shares by Type and Industrial Sector

	N	ω_{build}	$\omega_{machine}$	ω_{land}	$\omega_{structure}$	ω_{tools}	$\omega_{vehicle}$
Light manufacturing	237	0.468	0.222	0.243	0.042	0.036	0.037
		(0.131)	(0.153)	(0.163)	(0.027)	(0.035)	(0.031)
Heavy manufacturing	525	0.472	0.240	0.224	0.041	0.038	0.035
		(0.133)	(0.146)	(0.161)	(0.027)	(0.038)	(0.031)
Real estate	30	0.429	0.214	0.286	0.055	0.024	0.036
		(0.173)	(0.183)	(0.193)	(0.035)	(0.026)	(0.032)
Construction	121	0.448	0.224	0.259	0.050	0.022	0.041
		(0.153)	(0.174)	(0.181)	(0.030)	(0.024)	(0.034)
Transportation	88	0.512	0.195	0.210	0.046	0.027	0.049
		(0.160)	(0.160)	(0.160)	(0.031)	(0.024)	(0.035)
Electronics	259	0.467	0.229	0.239	0.033	0.055	0.030
		(0.111)	(0.120)	(0.147)	(0.019)	(0.048)	(0.026)
Non-transportation services	82	0.470	0.196	0.266	0.051	0.024	0.042
		(0.180)	(0.167)	(0.199)	(0.036)	(0.024)	(0.036)
Agriculture	13	0.532	0.177	0.217	0.046	0.029	0.044
		(0.129)	(0.136)	(0.120)	(0.013)	(0.024)	(0.036)
Overall	1,507	0.469	0.222	0.240	0.042	0.036	0.037
		(0.144)	(0.150)	(0.168)	(0.029)	(0.037)	(0.032)

Notes: The table displays the average input shares (ω_i), with standard errors in parentheses, for the six types of capital reported by firms in the DBJ database: buildings, machines, land, structures, precision tools, and vehicles. We sort firms into eight broad industrial sectors based on their 2-digit industry code. Light manufacturing includes handicrafts, food, textile, lumber/wood, paper/pulp, and printing firms. Heavy manufacturing includes those in the metal refining, smelting, and chemical production. Real estate includes leasing and rental companies. Construction includes construction, engineering, and dredging companies. Transportation includes automobile manufacturers, trucking, and railway companies. Electronics includes household appliances, software, and precision instruments producers. Non-transportation services includes wholesale/retailers and services firms outside shipping and transport. Agriculture includes fisheries, livestock, and farming.

FIGURE D.1. Distribution of Physical Capital Input Shares

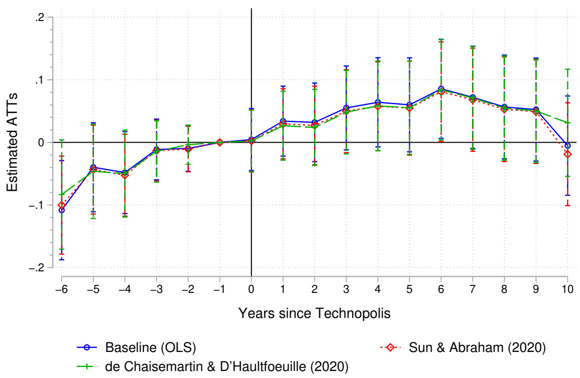


Notes: Each panel plots the distribution of capital input shares obtained from assuming a Cobb-Douglas physical capital aggregator in firm production and adapting the perpetual inventory method of Hayashi & Inoue (1991) to the DBJ data. Dashed red vertical lines indicate the average share. Our classification of long-lived asset firms is based on share of buildings used in production. Structures here refers to small buildings detached from the main plant site or non-enclosed spaces (such as a shed or outdoor well with roof). In cases where a firm is missing variables needed to construct the user costs underlying this method, we assign to that firm the input share of its nearest neighbor using a logit propensity score matching procedure based on firm size, age, and industrial sector. See text for details.

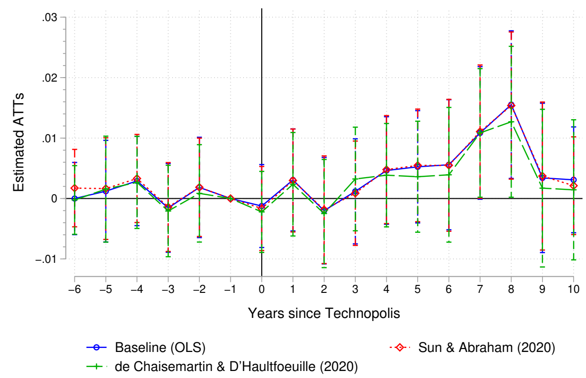
E Main Results Using Other Staggered DD Estimators

FIGURE E.1. Dynamic Effects of Technopolis by Staggered DD Estimator

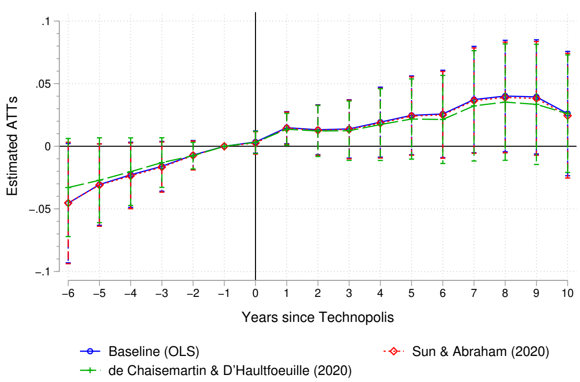
A. Bonus depreciation probability



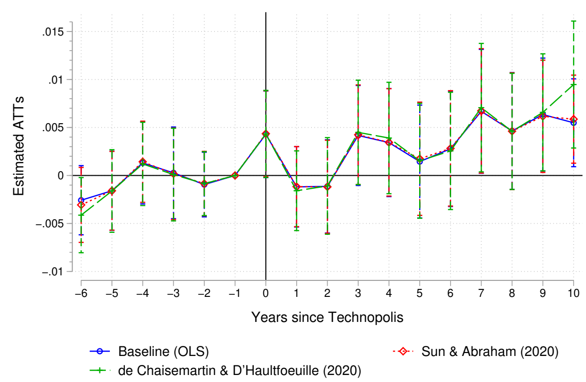
B. Cash flow



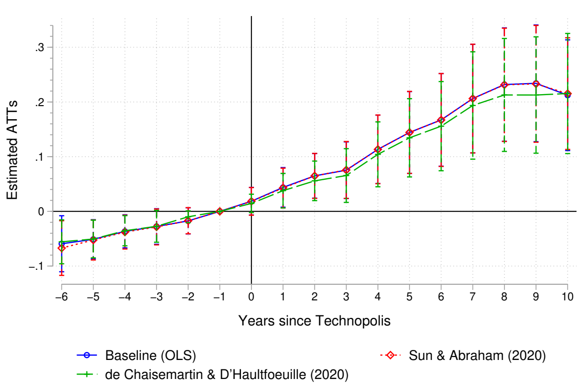
C. Employment



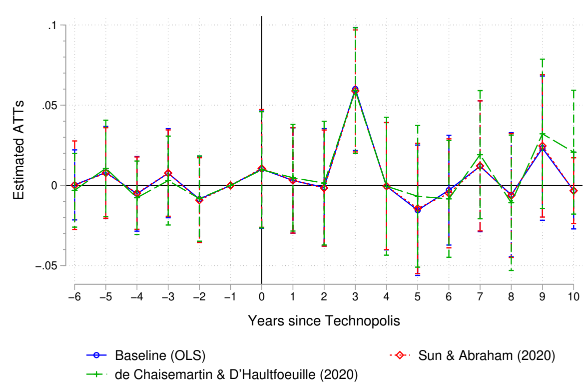
D. Construction in progress



E. Non-real estate assets



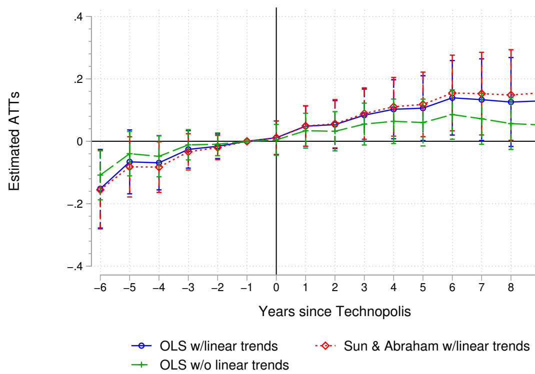
F. Long-term debt issuance



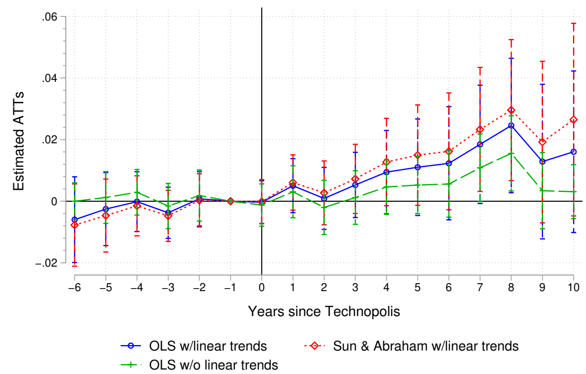
Notes: Each panel shows the dynamic response of an outcome of interest estimated via the staggered DD model in equation (4.2) using different estimators, including OLS (baseline), de Chaisemartin & D'Haultfœuille (2020), and Sun & Abraham (2021). Each regression includes HQ Census region × year fixed effects. With the exception of the bonus depreciation dummy and employment, each variable is deflated by the firm's book assets in 1975 before our estimation sample start date. Firm employment is scaled by its value in 1975. We bin the dummies at the end of the effect windows for $t = -6$ and $t = 10$. All dynamic effects are relative to one year before a firm becomes eligible for Technopolis. The bars show 95% confidence intervals obtained from standard errors clustered at the firm level. For the de Chaisemartin & D'Haultfœuille estimator we obtain standard errors from 1,000 bootstrap iterations. See text for details on the definition of each outcome.

FIGURE E.2. Robustness to Including Linear Firm Time Trends

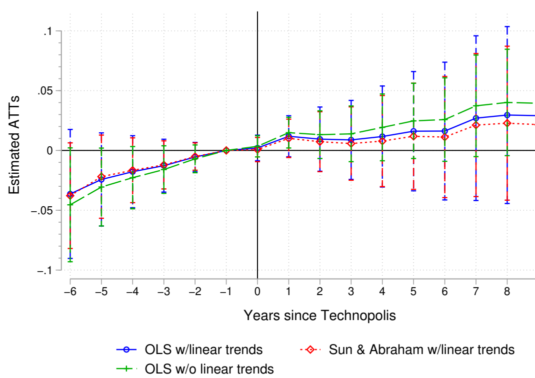
A. Bonus depreciation probability



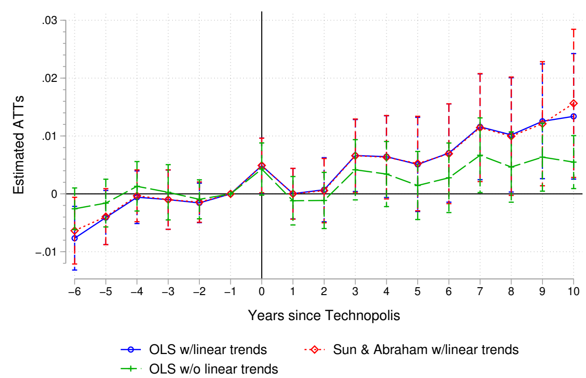
B. Cash flow



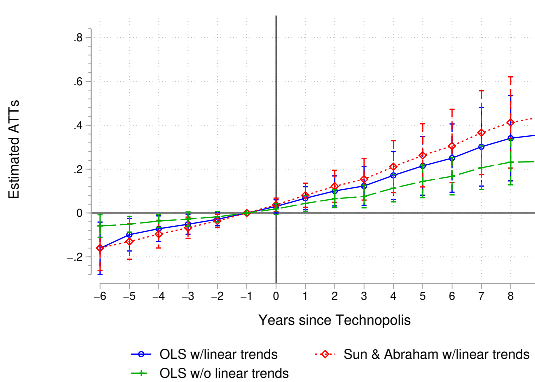
C. Employment



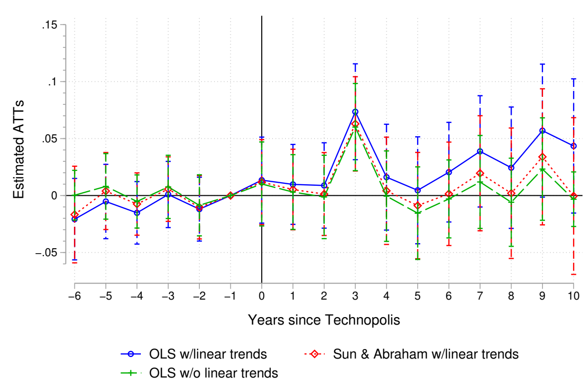
D. Construction in progress



E. Non-real estate assets



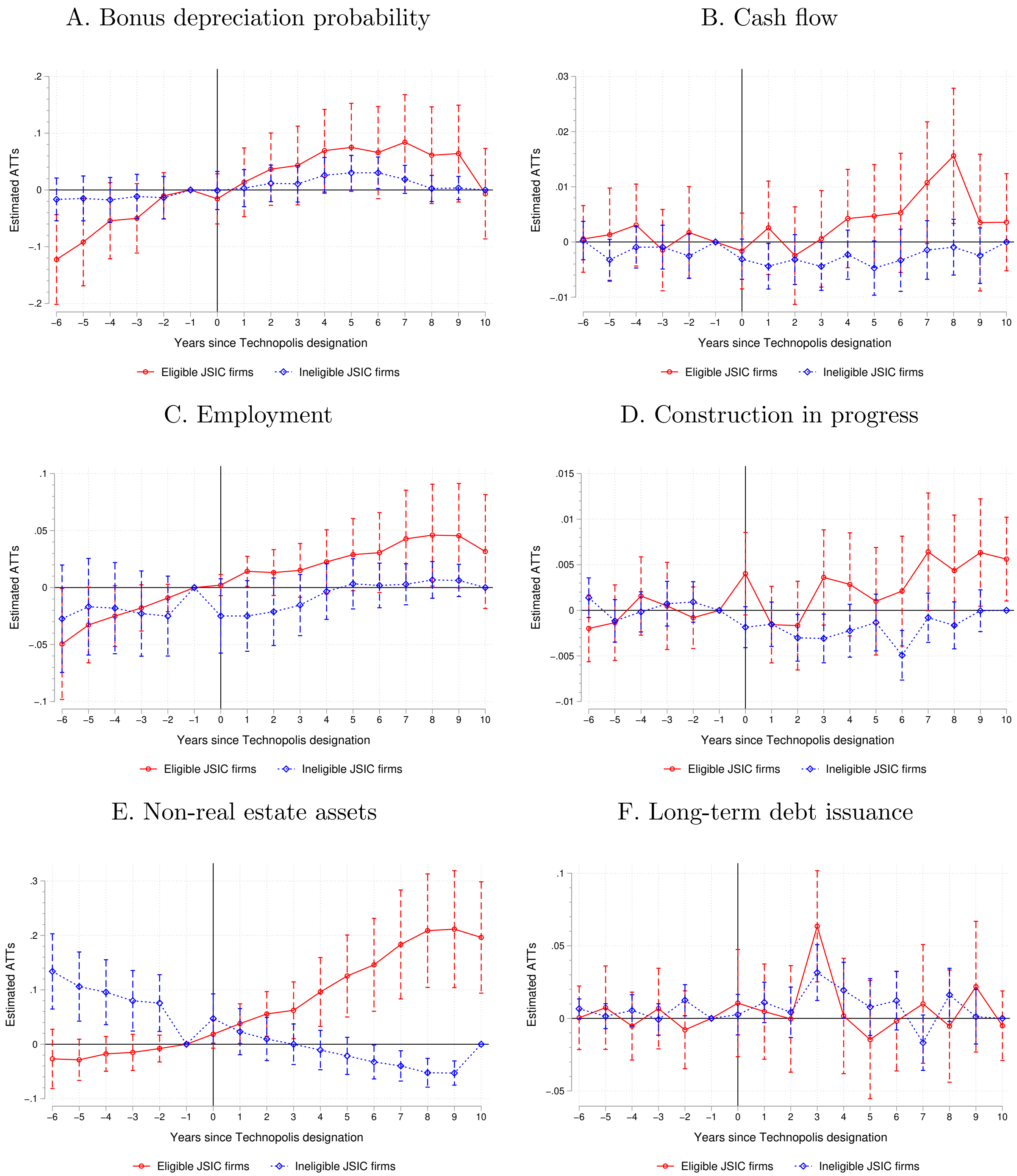
F. Long-term debt issuance



Notes: Each panel shows the dynamic response of an outcome of interest estimated via a version of the staggered DD model in equation (4.2) using either OLS or Sun & Abraham (2021). Each regression includes HQ Census region $\times$ year fixed effects. The blue and red lines plot estimates obtained from including linear firm time trends, while the green line shows our baseline estimates without including linear trends. With the exception of the bonus depreciation dummy and employment, each variable is deflated by the firm's book assets in 1975 before our estimation sample start date. Firm employment is scaled by its value in 1975. We bin the dummies at the end of the effect windows for $t = -6$ and $t = 10$. All dynamic effects are relative to one year before a firm becomes eligible for Technopolis. The bars show 95% confidence intervals obtained from standard errors clustered at the firm level. See text for details on the definition of each outcome. Note we do not provide estimates via de Chaisemartin & D'Haultfœuille (2020) or Borusyak, Jaravel, & Spiess (2021), because these estimators use not-yet treated firms as a control group for which the trends are not identified.

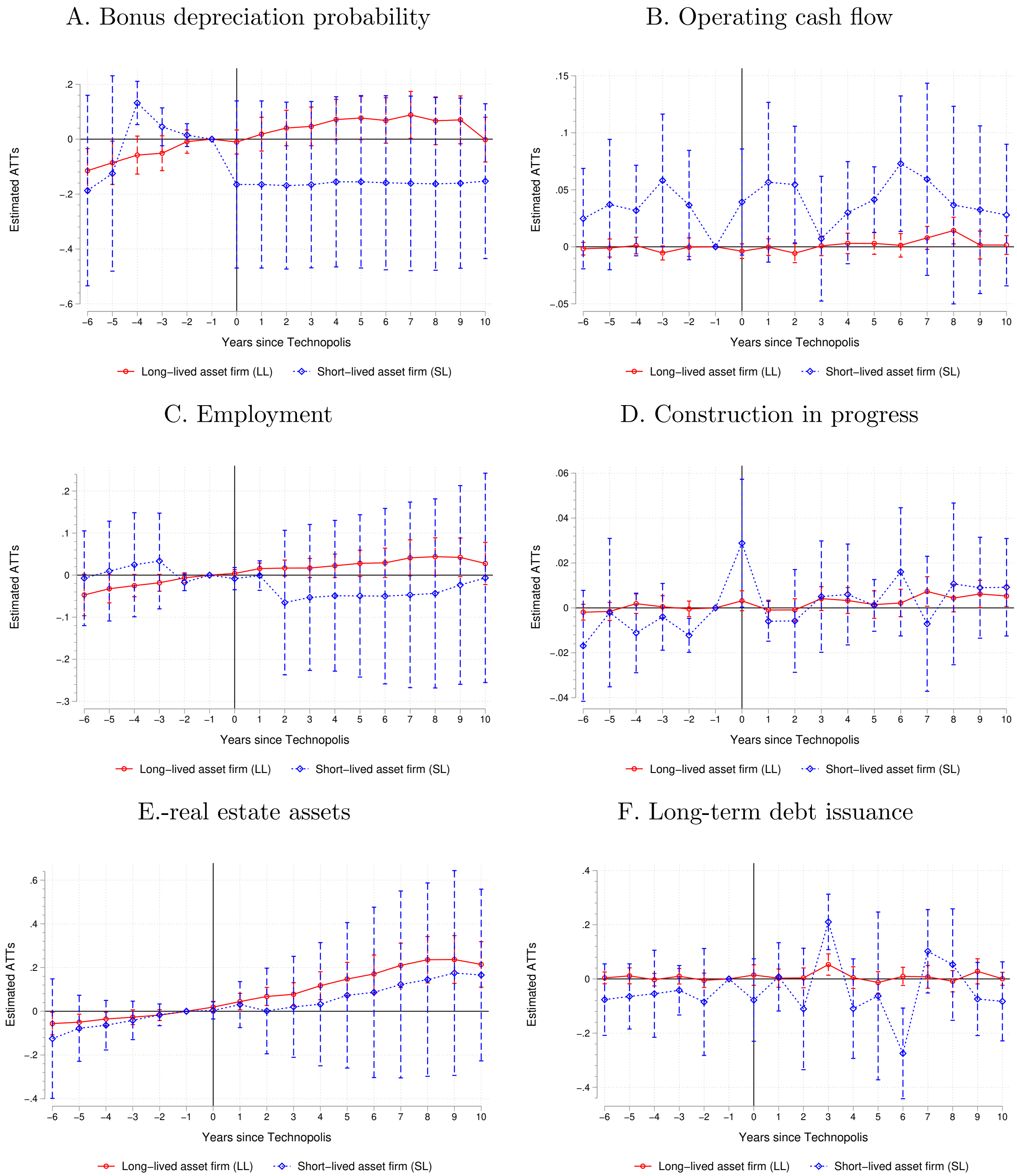
F Dynamic & Heterogeneous Effects

FIGURE F.1. Evolution of Local Spillovers to Untreated Firms



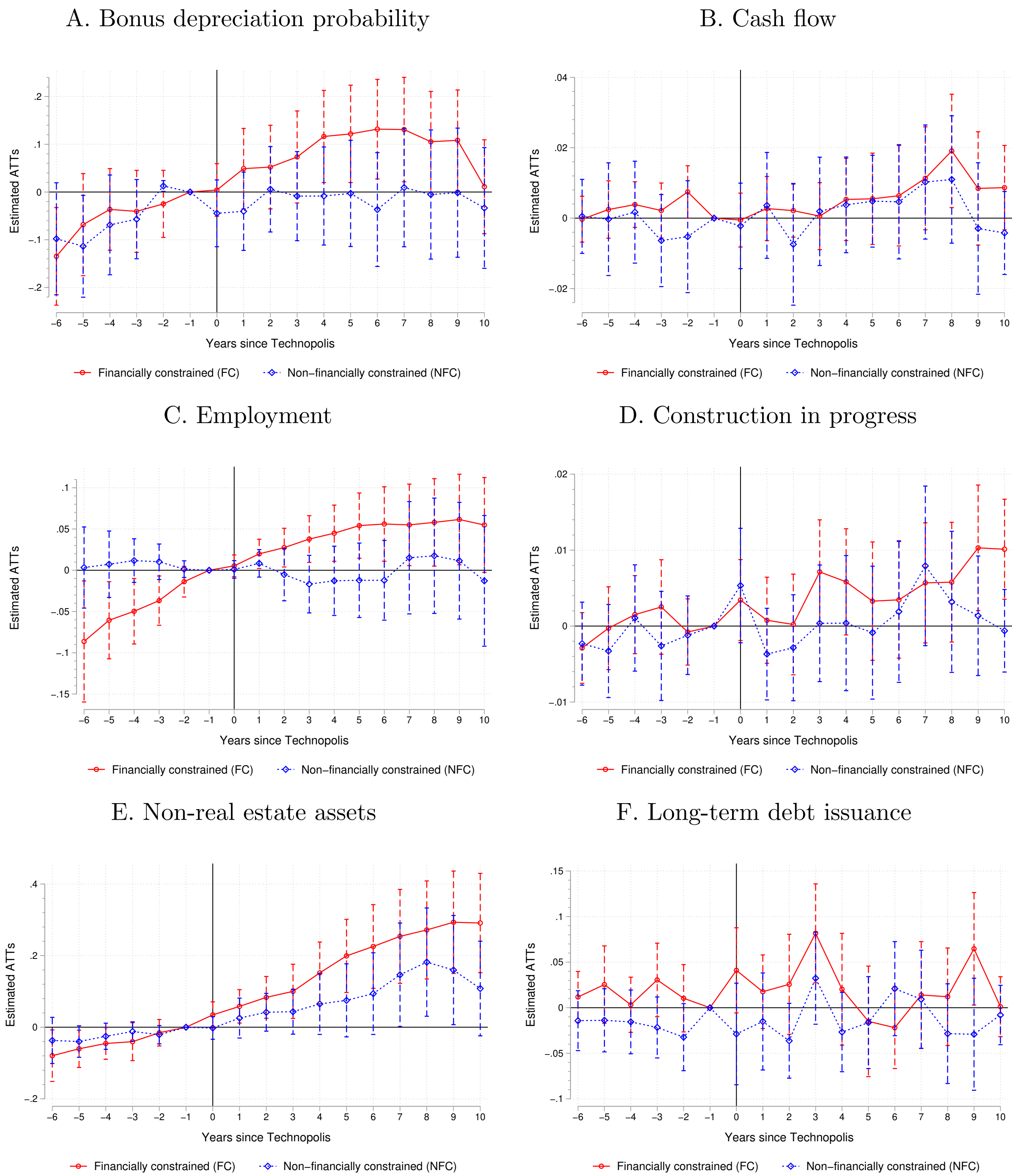
Notes: Each panel shows the dynamic response of an outcome of interest estimated via the staggered DD model in equation (5.1) using OLS. We report separate dynamic effects depending on whether the firm is eligible to claim bonus depreciation under Technopolis ($Treatment$), or if the firm is located in a Technopolis area but does not operate within an eligible JSIC ($TreatedCity$). We define firm-level eligibility according to the three criteria outlined in Section 4. Each regression includes HQ Census region × year fixed effects. With the exception of the bonus depreciation dummy and employment, each variable is deflated by the firm's book assets in 1975 before our estimation sample start date. Firm employment is scaled by its value in 1975. We bin the dummies at the end of the effect windows for $t = -6$ and $t = 10$. All dynamic effects are relative to one year before a firm becomes . The bars show 95% confidence intervals obtained from standard errors clustered at the firm level.

FIGURE F.2. Dynamic Effects by Reliance on Long-lived Assets



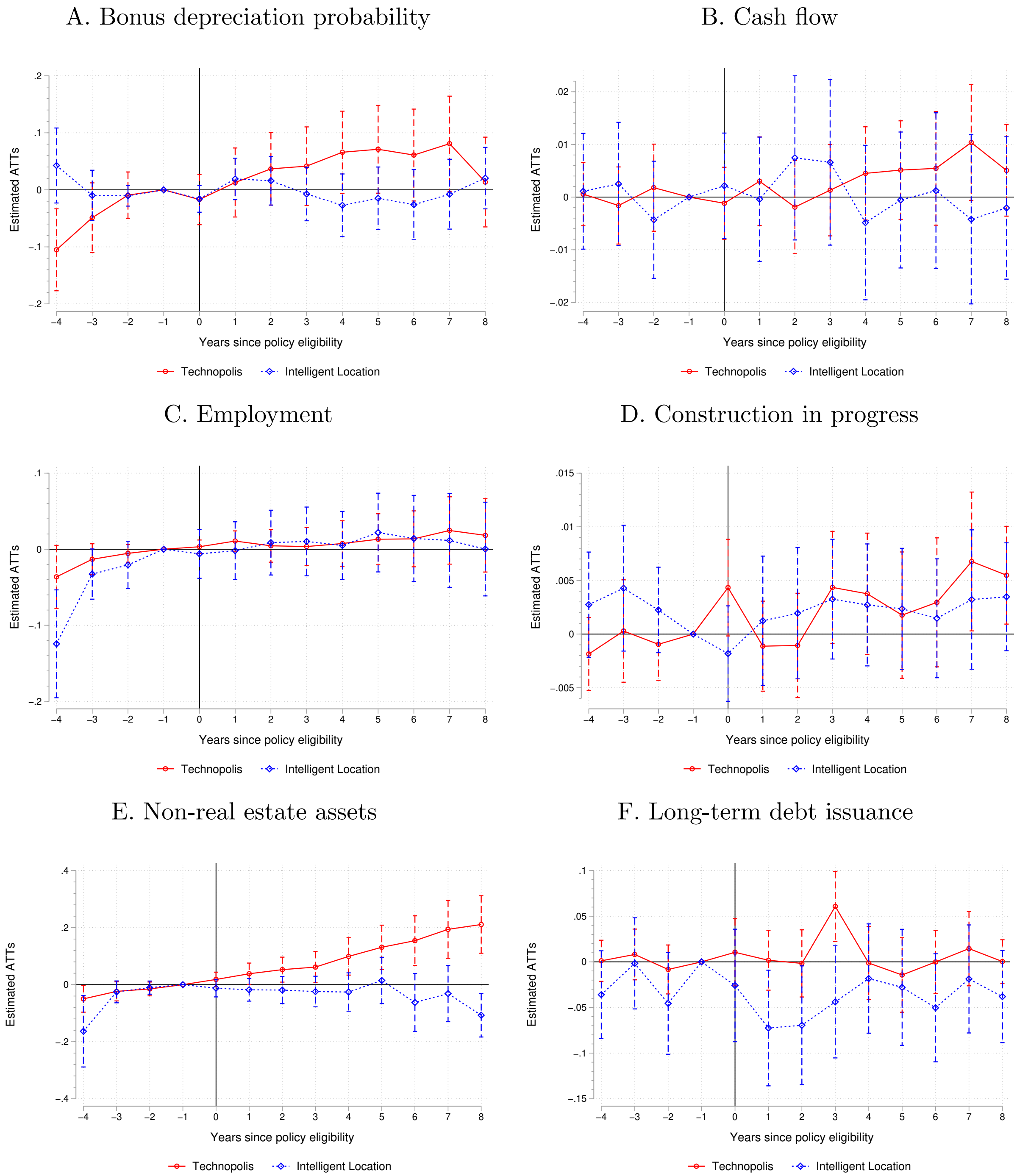
Notes: Each panel shows the dynamic response of an outcome of interest estimated via the staggered DD model in equation (5.5) using OLS. We report separate dynamic effects depending on whether the firm primarily relies on long-lived (LL) or short-lived (SL) assets. LL and SL firms are defined as in Section 5.3.1 and Appendix D. Each regression includes HQ Census region × year fixed effects. With the exception of the bonus depreciation dummy and employment, each variable is deflated by the firm's book assets in 1975 before our estimation sample start date. Firm employment is scaled by its value in 1975. We bin the dummies at the end of the effect windows for $t = -6$ and $t = 10$. All dynamic effects are relative to one year before a firm becomes eligible for Technopolis. The bars show 95% confidence intervals obtained from standard errors clustered at the firm level.

FIGURE F.3. Dynamic Effects by Financial Constrainedness (Size-Age)



Notes: Each panel shows the dynamic response of an outcome of interest estimated via the staggered DD model in equation (5.6) using OLS. We report separate dynamic effects depending on whether the firm is financially constrained (FC) or non-financially constrained (NFC) according to the size-age index of Hadlock & Pierce (2010) described in Section 5.3.2. Each regression includes HQ Census region × year fixed effects. With the exception of the bonus depreciation dummy and employment, each variable is deflated by the firm's book assets in 1975 before our estimation sample start date. Firm employment is scaled by its value in 1975. We bin the dummies at the end of the effect windows for $t = -6$ and $t = 10$. All dynamic effects are relative to one year before a firm becomes eligible for Technopolis. The bars show 95% confidence intervals obtained from standard errors clustered at the firm level.

FIGURE F.4. Dynamic Effects of Multiple Policy Treatments



Notes: Each panel shows the dynamic response of an outcome of interest estimated via the staggered DD model with multiple policy treatments in equation (5.7) using OLS. We report separate dynamic effects Each regression includes HQ Census region × year fixed effects. With the exception of the bonus depreciation dummy and employment, each variable is deflated by the firm's book assets in 1975 before our estimation sample start date. Firm employment is scaled by its value in 1975. We bin the dummies at the end of the effect windows for $t = -4$ and $t = 8$. All dynamic effects are relative to one year before a firm becomes eligible for either Technopolis (red) or Intelligent Location (blue). The bars show 95% confidence intervals obtained from standard errors clustered at the firm level.

Appendix References

Borusyak, K., X. Jaravel, & J. Spiess (2021): "Revisiting Event Study Designs: Robust and Efficient Estimation," *mimeo*, LSE.

Callaway, B. & P.H.C. Sant'Anna (2021): "Difference-in-Differences with Multiple Time Periods," *Journal of Econometrics*, 225(2): 200-230.

de Chaisemartin, C. & X. D'Haultfœuille (2020): "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review*, 110(9): 2964-2996.

Hayashi, F. & T. Inoue (1991): "The Relation Between Firm Growth and Q with Multiple Capital Goods: Theory and Evidence from Panel Data on Japanese Firms," *Quarterly Journal of Economics*, 59(3): 731-753.

LaPoint, C. (2020): "You Only Lend Twice: Corporate Borrowing and Land Values in Real Estate Cycles," *mimeo*, Yale.

Ministry of International Trade and Industry (1995): "The Catalogue of Equipment and Facilities Eligible for Bonus Depreciation," MITI Kinki Office.

Sun, L. & S. Abraham (2021): "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects," *Journal of Econometrics*, 225(2): 175-199.

Zwick, E. & J. Mahon (2017): "Tax Policy and Heterogeneous Investment Behavior," *American Economic Review*, 107(1): 217-248.