Place-Based Policies and the Geography of Corporate Investment *

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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 take-up and efficacy of industrial place-based policies by studying a national 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. The policy produced a welfare gain of $56.72 billion, or 40% of total annual corporate profits. For eligible firms, plant-level hiring in ineligible areas outstripped that in eligible areas, suggesting reallocation of resources within firms' internal capital and labor markets mitigates the spatial misallocation inherent in subsidizing low marginal productivity areas.

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

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1 Introduction

A key feature of modern industrial policies is that they include provisions to counteract regional inequality in income and employment opportunities (Juhász, Lane, & Rodrik 2023). Regional divergence has become a more pressing concern for policymakers in economies like the U.S., which since the late 1970s has experienced a shift from heavy manufacturing towards a service-based economy, leading to declines in living standards for residents of former rustbelt cities (Fort, Pierce, & Schott 2018). The Regional Technology and Innovation Hubs Program, as part of the 2022 U.S. CHIPS and Science Act, offers incentive packages for local governments to facilitate the creation of regional high-tech hubs and STEM jobs, with a focus on developing and manufacturing critical technologies like semi-conductors at locations outside major cities.[1] Can targeted industrial policies like those in the CHIPS Act be designed to deliver long-lasting investment and increased opportunities for residents of economically struggling areas while improving aggregate welfare?

We explore this question and the tradeoffs between national productivity and regional inequality inherent in place-based policies (PBPs) by examining a national tax break 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 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 buildings used in business operations. Technopolis combined common elements of tax subsidies allocated to specific companies, as in the private-public partnerships funded by CHIPS, with those of broad-based policies that create catchment areas within which special tax incentives apply (e.g. Opportunity Zones in the U.S.).

Using staggered difference-in-differences (DD) and triple differences specifications which define treatment at the firm level based on industry, plant locations, and reliance on long-lived capital inputs, 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.[2] For listed firms, capital shares within a firm's internal network

[1] The U.S. Economic Development Administration under the Department of Commerce provides a detailed breakdown of tech hubs awarded funding through CHIPS: https://www.eda.gov/funding/programs/regional-technology-and-innovation-hubs. $500 million has been allocated to 31 hubs as of October 2023, with $10 billion authorized over the next ten years.

[2] A prominent example of this type of corporate behavior is the aborted 2018 deal between the state of Wisconsin and Foxconn, a Taiwanese multinational electronics manufacturing firm. Foxconn initially received a pledge of $4 billion in subsidies and tax credits in exchange for a promise to bring 13,000 workers and $10 billion in investment to Racine, Wisconsin. By the end of 2019, Foxconn had hired only 281 workers and invested 2.8% of the promised $10 billion into an empty facility (Tabak 2022).

are stable three decades after the bonus depreciation incentives expired. Corporate investment was concentrated in construction projects on existing production sites. We find granting firms Technopolis eligibility generated a 0.29 standard deviation increase in construction spending, and a 0.40 standard deviation increase in non-real estate (i.e. machine) purchases.

Firms also increased 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. We conduct a welfare analysis in the spirit of Busso, Gregory, & Kline (2013) and Lu, Wang, & Zhu (2019) which accounts for gains in wages, corporate profits, and tax revenues due to the policy. We calculate that Technopolis generated a real present value surplus of $56.7 billion, or roughly 40% of one year's worth of total profits earned by listed firms. Our detailed balance sheet data allow us to decompose these gains and show that the capital subsidies boosted corporate profits, thereby expanding the size of the corporate income tax base. We conclude Technopolis was highly effective from an overall cost-benefit accounting perspective relative to similar manufacturing subsidies and bonus depreciation schemes enacted elsewhere. Applying a partial equilibrium accounting approach which combines 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 $16,000 per corporate job created.[3]

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). Similar to the U.S., 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 the Tokyo commuting zone.[4]

PBPs like Technopolis are usually enacted under a paternalistic, distributional rationale to combat regional divergence. But, stimulating struggling economies entails redirecting tax revenues to low marginal productivity areas, which may lead to aggregate welfare losses in the presence of agglomeration externalities (Gaubert 2018). Okun (1975) famously introduced a "leaky bucket" metaphor in his treatise on equity-efficiency tradeoffs to describe how government spending (the "water") aimed at the poor might flow to higher-income individuals. Consistent with this leakage concept, within policy-eligible firms, we show hiring in untreated areas is over six times more responsive to the physical capital subsidy rate than in treated areas (a semi-elasticity of 15.4 vs. 2.3, respectively), indicating that firms redirect cash flows from bonus claims away from peripheral labor markets towards manufacturing jobs in major cities. Firms claiming subsidies are 15 p.p. less likely

[3] Our cost-per-job estimates are comparable to those cited in the literature, which instead rely on an assumed or imputed subsidy rate, such as the $20,000 per job estimate of Garrett, Ohrn, & Suárez Serrato (2020) for all bonus claims offered in the U.S. between 2002 and 2012. In Appendix H, we conduct a sensitivity analysis for our cost-per-job estimates and compare our estimates to numbers obtained from firm-level place-based policies elsewhere.

[4] We present this result for Japan in Appendix A.5.

to hire in Technopolis-eligible areas and just as likely to instead hire in ineligible areas. Aggregate TFP is much higher when firms allocate resources to set marginal products equal across plants (Hsieh & Klenow 2009), and Technopolis created efficiency "wedges" by subsidizing manufacturing sites with lower marginal products of capital. Multi-plant firms undo the spatial misallocation associated with PBPs, contributing to the relatively large welfare gains we compute.

To highlight the crucial role of multi-plant firms' physical capital structure in the effects 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: buildings, land, structures, machines, tools, and vehicles. 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 the intent-to-treat estimates and imputed subsidy rates common in the literature 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 2023) in staggered DD contexts.

Much of the latest empirical research 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.[5] 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 (2023) conclude these tax incentives had no statistically significant impact on resident employment, earnings, or poverty rates. Chen, Glaeser, & Wessel (2019) document minimal capitalization into single family home prices. Arefeva et al. (2023) instead find designated OZ Census tracts experienced increased employment growth of 2-4 p.p. between 2017 and 2019.[6]

[5] 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).

[6] Xu (2022) also compares designated tracts to eligible, undesignated tracts and uncovers an increase in real estate investment within OZs, but with the unintended side-effect of a decline in local non-tradable sector entrepreneurial activity. Corinth & Feldman (2022) instead use on a regression discontinuity design exploiting the income threshold determining tract eligibility but find no increase in investment or consumer spending in OZs.

Our paper is the first to evaluate bonus depreciation as a broad place-based policy. We emphasize two main features which distinguish our setting from related local business incentive schemes. First, our results point to the importance of providing *immediate* rather than deferred financial incentives for inducing firms to invest 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 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, and much like under current CHIPS programs, eligible locations are selected for their manufacturing capacity and proximity to research universities, with incentives funded through national rather than local budgets.

Whereas the vast majority of research on PBPs covers targeted state and local tax subsidies and restricts attention to short-run effects due to data limitations (Bartik 2020), the historical nature of the Technopolis episode allows us to examine long-run effects on productivity and welfare. 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. 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 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 accept subsidies without increasing local activity, echoing our findings of labor market leakage. In recent work, Kennedy & Wheeler (2022) 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.

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 2024), 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 eligible firms' hiring was concentrated in Technopolis *ineligible* areas, implying spillovers within internal corporate labor markets.

Research on PBPs has overwhelmingly focused on labor market outcomes. In this paper we focus on how tax incentives can shift the spatial distribution of labor and capital *within* large firms, either by lowering the cost of capital at specific locations, or by ameliorating frictions in capital markets. Such frictions might include financial constraints, as emphasized in a large corporate finance literature (e.g. Giroud & Mueller 2015, 2017, 2019), investment adjustment costs or "time to build" (Cooper & Haltiwanger 2006), and the costs of transporting tangible assets between locations (Ma, Murfin, & Pratt 2022). We find intra-firm transport costs are a critical driver of local tax policy take-up and investment. An eligible firm is 1% less likely to claim bonuses for every 10 km increase in commuting distance between its network of existing plants and the nearest Technopolis area. Regional tech hubs are more likely to attract corporate investment if they are not placed too far away from the larger cities favored by large multi-plant firms.

When we rank firms based on balance sheet size and age, we find that smaller, younger firms drive the take-up of bonus claims, investment, and hiring, consistent with such firms applying a higher discount rate to future cash flows. Zwick & Mahon (2017) show sectors using longer-lived assets like industrial equipment exhibit larger investment responses to the 2001 and 2008 U.S. bonus depreciation reforms, consistent with models featuring fixed adjustment costs and/or financing constraints.[7] We recover firms' capital input shares using the perpetual inventory methods of Hayashi & Inoue (1991) to rank firms based on their reliance on long-lived vs. short-lived assets. Buildings account for 38% of the capital input share for the average listed firm in our sample. 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.[8] The outsize share of properties in firm production, combined with the maximum bonus depreciation claim of 15% for buildings under Technopolis, renders relocation and outright ownership of new plants (or expansions of existing plants) in treated regions substantially more attractive. In documenting that bonus write-offs encourage new building construction, we complement Basu, Kim, & Singh (2022), who show that firms substitute towards new equipment in response to such incentives.

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 locate) and the intensive margin – that is, how many resources to allocate to a particular location. Gaubert (2018) builds a model with agglomeration in which firms sort across cities on the extensive margin and argues PBPs which subsidize smaller cities have negative aggregate effects. In Fajgelbaum et al. (2018), firms sort into states which offer lower income tax rates, as evidenced in Giroud & Rauh (2019), and tax competition between states diminishes aggregate welfare. Like Jia (2008) and Holmes (2005, 2011), Oberfield et al. (2023) 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.

[7] There is a voluminous empirical literature analyzing the investment response to corporate tax breaks, dating back to Hall & Jorgenson (1967). 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), Yagan (2015), and Moon (2022) on capital gains taxes; House & Shapiro (2008), Edgerton (2010) on bonus depreciation. 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.

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

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. 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 large output responses to policy changes. Our findings rationalize putting physical capital back into models of spatial firms to assess the aggregate effects of place-based policies.[9]

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 presents 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 discusses fiscal cost-per-job calculations and welfare implications. 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. We relegate our analysis of the Intelligent Location policy to Appendix I, but overall find that it had little, if any, additional effects beyond the rollout of Technopolis given that it offered physical capital subsidies to firms in upstream industries which do not intensively use physical capital inputs.

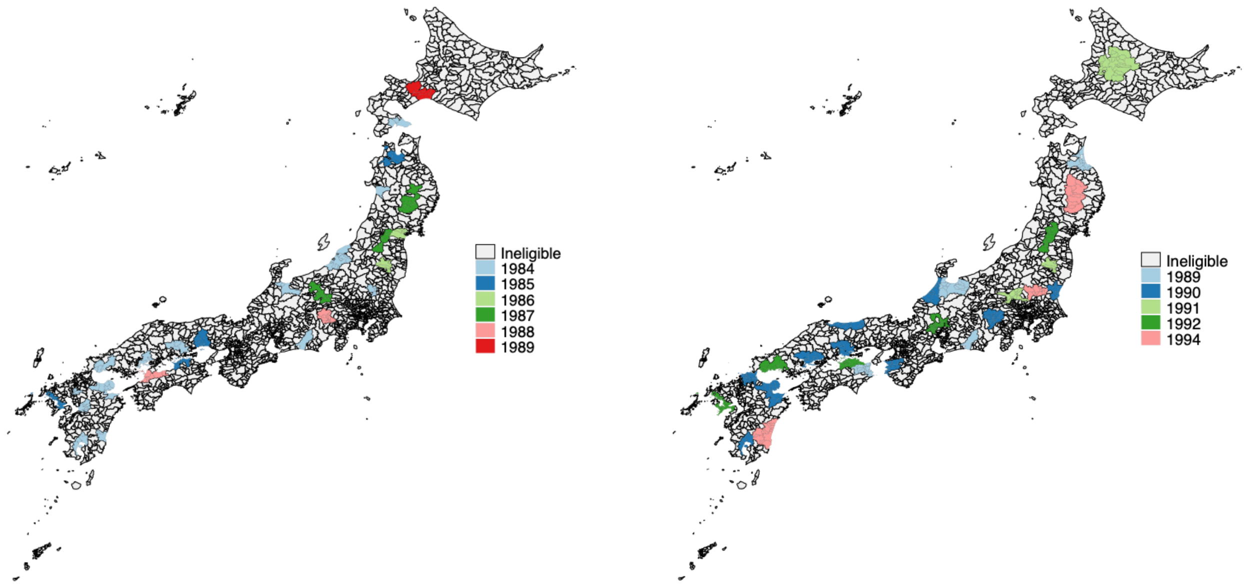
For both policies, we obtain the schedule of bonus depreciation rates from Ministry of International Trade and Industry (1995), which describes eligible asset classes and facilities at the 4-digit Japan Standard Industry Classification (JSIC) level. We collect the list of treated jurisdictions from the Japan Location Center (1999) history of the two policies. We provide in 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.[10] We now summarize the tax incentives

[9]Other papers in the theoretical spatial firms literature include Kerr & Kominers (2015), who study the rise of industry clusters like Silicon Valley in a model where agglomeration forces decay with distance due to interaction costs. Walsh (2019) shows 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.

[10]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 1). 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.

FIGURE 1. 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).

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 1 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.[11] In practice this meant that

[11]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." We present results using 1980 boundaries in Appendix G.4.

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).

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 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.

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).

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. For the typical firm in our sample, we estimate a local CAPX subsidy of between 2% and 3% from claiming Technopolis bonuses within the first few years of the program. The subsidy rate is linearly increasing in the share of investment in long-lived physical assets: a fact we exploit in our empirical research designs.

The final dimension of Technopolis eligibility is the industry classification of the corporate tax unit.[12] 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.1. 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.

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,

[12]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.

while also expanding the catchment areas for these clusters. Among the 26 Technopolis clusters, 15 regions were also designated Intelligent Locations. Figure 1 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.

How economically distinct were the sites selected by the Technopolis and Intelligent Location policies? In Appendix A.3.2, we compare local macroeconomic characteristics of policy sites to non-policy sites in 1980, prior to the implementation of Technopolis. Policy sites have initially greater manufacturing sector employment and value-added per worker (MPL), but lower value-added per machine (MPK), which underpinned the decision of the government to offer subsidies for physical capital rather than for labor. However, compared to the unsubsidized major metro areas, the regional hub cities within each Technopolis feature lower productivities of both labor and capital, and there is no evidence of regional convergence resulting from the Technopolis and Intelligent Location policies. We provide a more complete historical narrative surrounding the selection of industry cluster sites in Appendix A.3.1.

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 spatial bonus depreciation schemes.

3.1 Census of Manufactures

The first layer of our dataset consists of plant-level microdata from 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 maximize time coverage, we subset our sample to all plants with four or more employees. The COM data are valuable for studying responses to the Technopolis and Intelligent Policy initiatives given previous findings 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 employment at manufacturing sites, the dollar amounts of the wage bill, value added, inventory, shipments, PPE, and cost of intermediate goods used in production. In our analysis of internal firm labor market responses in Section 5.4, we divide employment into Technopolis-eligible and ineligible areas. Accounting for firm fixed effects is particularly important, because firms may differ in their responses to 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. 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.

3.2 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.

Key to our analysis are the variables in DBJ pertaining to physical capital investment such as the book value of properties, plants, and equipment (PPE), which can be decomposed into six categories: buildings, machines, land, structures, precision tools, and vehicles. 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.

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 from 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 *yūhō* in Japanese) – and firms are required to report the municipality of any operating locations, regardless of whether the property is owned or rented.[13] 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.[14]

We hand-match COM plants to their parent DBJ firms for the years 1986 – 2000 based on the Japanese name of the parent firm in 1997 (the first year for which the name string is 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.[15]

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.[16] The relatively small match rate between DBJ and COM arises because COM only surveys firms engaged in manufacturing, while DBJ includes listed firms in all non-FIRE sectors of the economy.

The pecking order theory of Myers & Majluf (1984) would imply that firms substitute debt and equity issuance with cash flows from bonus depreciation claims to finance their operations. We test

[13]DBJ obtains the corporate balance sheet information from the annual *yūhō* 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 *yūhō* 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.

[14]We impose modern municipal boundaries using the 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 findings are qualitatively similar when we instead impose historical 1980 municipal boundaries to assign treatment status. We address differences in geography definitions in Appendix G.4.

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

[16]The matched DBJ-COM sample increases to 1,013 firms if we drop the requirement that firms report non-missing total assets for five consecutive years. Of the 870 firms in our sample, 740 have a 4-digit industry code within the manufacturing sector. These 740 firms form our sample for the analysis of leakage effects in Section 5.4.

this implication by merging in from Nikkei NEEDS FinancialQUEST the monthly closing date stock price and shares outstanding for each firm in our DBJ sample. For firms in our sample time period which remain currently active, we merge between the two databases via the listed stock code. For firms which are no longer active – for instance, if they were delisted or acquired by another firm – we match on the standardized name string (e.g. by deleting suffixes like "CO" or "LTD"). We hand match the stock series to balance sheets by tracking the company history for the remaining 159 inactive firms that cannot be directly merged between Nikkei and DBJ due to name changes.

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.[17] 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 (2021) 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 3 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 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:

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

[17] We discuss in Appendix G.3 robustness to using transformations of outcome variables such as $\log(1 + x)$ and the inverse hyperbolic sine function.

TABLE 3. 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 *yūhō*).

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 analysis in Section 5.1 using aggregated COM data, we assign eligibility at the city $\times$ 2-digit manufacturing sector level, so $Treatment_{i,c,t} = Treated_{i,c} \times Post_{c,t}$, where $Treated_{i,c}$ is equal to one if city c is an eligible city and i is a 2-digit sector containing at least one eligible 4-digit industry code, 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 *yūhō* the firm operates at least one plant located in an eligible Technopolis area.[18]

(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.

These three criteria yield a 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

[18] 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 A.3), 43% 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.

$Post_{j,t} = 1$ if $t \geq 1984$, and $Treated_{j,k} = 1$ if the firm is in an eligible industry. Our DD model in (4.1) is a staggered DD where several potential within-firm treatments are stacked up via $Post_{j,t}$.[19] We relax criterion (i) in Section 5.3 by making treatment a function of plant distance to Technopolis sites rather than conditioning on the firm already have a presence in a Technopolis.

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 Appendix I, 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):

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

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 (2023) [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 (National Institute of Science and Technology Policy 1998). We accommodate anticipation effects by shifting forward $\beta_t \rightarrow$

[19] 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. We find in Section 5.3 that, conditional on a firm's distance to the nearest Technopolis, industry eligibility drives most of the intensive margin response to the policy.

β_{t+1} in event study specification (4.2).[20] 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.[21] *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.[22]

5 Firm Employment & Investment Responses

In this section, we report our main results from estimating the staggered DD models described in Section 4. 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 and outlays towards construction projects and non-real estate assets, while substituting away from land which does not depreciate. These effects are driven by (i) firms relying on relatively long-lived assets as production inputs, (ii) younger and smaller firms, and (iii) firms with pre-existing plants proximal to a policy area.

5.1 City-by-Industry Level Evidence of Extensive Margin Responses

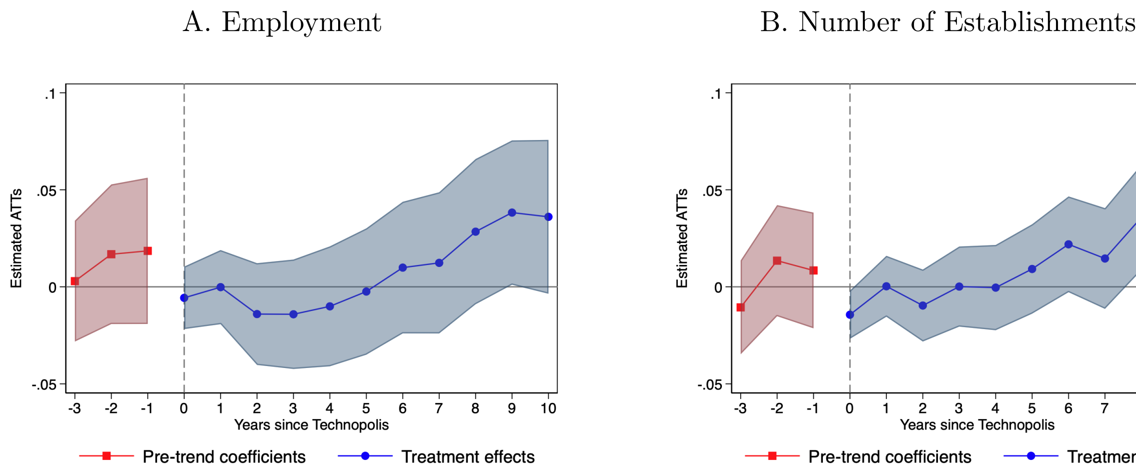
We begin by aggregating the Census of Manufactures to the city c × 2-digit industry i level and estimating versions of (4.1), where $Treatment_{i,c,t} = Treatment_{i,c} \times Post_{c,t}$. Figure 2 plots the

[20]As recommended by Borusyak, Jaravel, & Spiess (2023), we do not shift forward the β_t for anticipation effects when we test for parallel trends via separate regressions on untreated observations. We also compute standard errors by taking leave-one-out averages across the cohort treatment effects, which accounts for small cohorts of treated observations and results in more conservative standard errors.

[21]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.

[22]We collect information on non-spatial bonus depreciation incentives offered under the pre-Technopolis tax code to determine which firms in our sample would have a decreased incentive to shift resources to a Technopolis site. Controlling for pre-reform bonus access has no quantitatively material effect on our results. This is unsurprising, because bonus rates offered through Technopolis were more generous than those in the pre-existing tax code.

FIGURE 2. City × 2-Digit Manufacturing-Level Dynamic 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 (2023). 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 municipal boundaries using the historical city code crosswalk available through RIETI (Kondo 2019). See text for details on the definition of each outcome.

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 sectoral employment and establishments.[23]

The event study analysis reveals a slow-moving gap in the evolution of employment and plant creation between Technopolis eligible cities and ineligible cities. For employment, this gap widens starting eight years after the introduction of tax incentives ($\widehat{\beta}_9$). Ten years after the reform, employment is 4% higher in eligible sites, while the number of establishments is 5% 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.[24]

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. Technopolis was enacted in the background of one of the largest real estate booms in modern history, and eligible areas both

[23]To construct this city × 2-digit industry panel, we use modern industry classifications and crosswalk the 2-digit manufacturing codes across the historical systems instituted in 1980, 1985, 2002, and 2008.

[24]While we observe PPE at the plant level in COM, we cannot aggregate up to a consistent definition of PPE over time 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.

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 confidence intervals expand because our sample drops down to only 375 cities for which we have CRE appraisal data.[25] 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 Corporate 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, employment, investment, and debt issuance.

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 3 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 bank loans payable + bonds outstanding). 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.

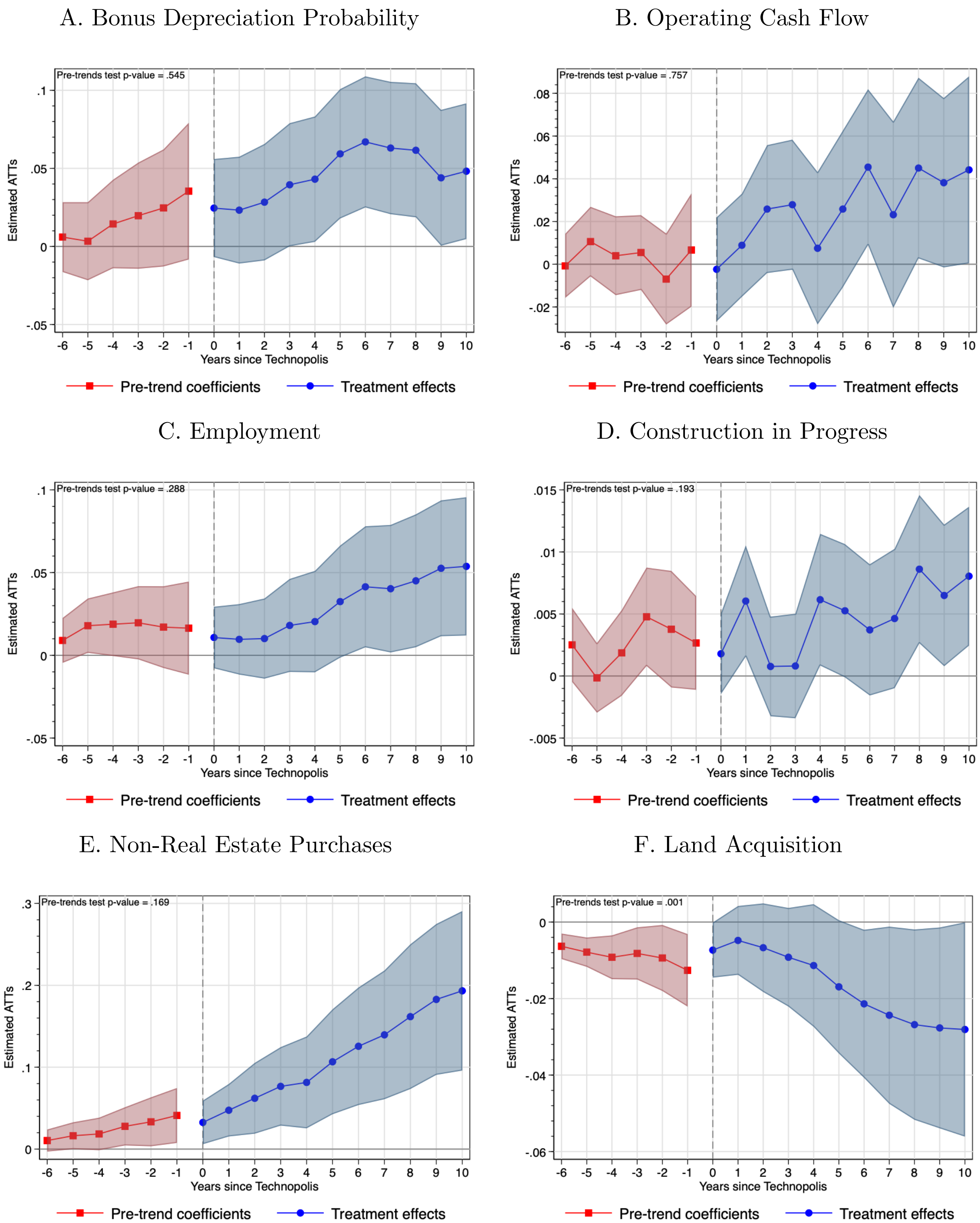
We focus on bonus depreciation claiming on the extensive margin given that 77% of firm-years feature zero net income from bonus depreciation. We deflate monetary variables by the value for that firm in the filing year before our sample starts (1975). Hence, the effects are scaled so that $\widehat{\beta}_t$ 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.[26]

The first panel in Figure 3 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

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

[26]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.

FIGURE 3. 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 (2023). 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.

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.[27] 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.[28] 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 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.[29]

The investment responses in Figure 3 are economically sizeable. The peak effect of Technopolis eligibility on purchases of non-real estate assets is 0.29 which is 40% of the standard deviation of new 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 high-profile place-based tax breaks, like the recent deal between Wisconsin and Foxconn, at incentivizing firms not to "toe dip" (Tabak 2022).

Table 4 establishes the robustness of our results to the inclusion of a battery of controls for

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[27]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*.

[28]Our results are qualitatively similar, but larger and more precisely estimated, when we use male full-time employment rather than overall firm employment as the outcome variable. Focusing on male employment is common in studies of the labor market, since female employment is highly cyclical and more closely related to fertility decisions than economic fundamentals. We estimate a dynamic effect on male employment that starts out at 4% and grows to 9% after 10 years of the policy regime. We do not adopt male employment as our main measure of job creation to maintain comparability of our welfare estimates in Section 6 and cost-per-job estimates in Appendix H to those computed in other studies. Male employment is also missing as a line item for around 14% of our sample.

[29]The p-values on the pre-trends tests for the other outcomes we consider in Figure 3 are 0.757 for operating cash flow, 0.288 for employment, 0.193 for construction, 0.169 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.

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. 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.

We do not include industry fixed effects in our baseline 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. Our results are qualitatively similar, albeit with smaller point estimates, when we include 1-digit industry code × year fixed effects.[30] In our baseline specifications we cluster standard errors at the firm level, since $Treatment$ as defined in Section 4 is determined by both the industry classification of the firm and its network of plant locations. Our results are robust to clustering by 4-digit JSIC × HQ city group, which produces slightly wider confidence intervals for most outcomes.

Comparing the point estimates in Panel B of Table 4 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 4 we still uncover positive responses of bonus claiming, construction, and non-real estate purchases 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 eligibility. In particular, OCF includes cash flow from bonus claims, so it is mechanically related to the take-up behavior induced by Technopolis.[31] We discuss results for other firm outcomes in

[30] The agriculture, real estate/construction, transportation activities, services/tradables sectors all contain zero 4-digit industries eligible for Technopolis bonuses. Eligibility is instead highly concentrated among the light manufacturing (27% eligible), electronics (65% eligible), and heavy manufacturing (42% eligible) sectors. As a result, the Technopolis eligible 4-digit industries are concentrated in eleven 2-digit industry codes.

[31] See Lian & Ma (2021) for a discussion on how to construct operating cash flow (OCF) and how it differs from EBITDA. The estimates in Table 4 insubstantially change if we instead use lagged financial controls to partially address this issue. 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 3), 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.

Appendix G.1, and compare first stage effects of bonus depreciation eligibility across different measures of firm cash flow in Appendix G.2.

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 5 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 purchases, and employment. 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 investment; 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.

Despite finding no clear evidence of local spillovers to ineligible corporate firms, it is possible that the economic activity spurred by Technopolis propagated to untreated parts of the country through inter-regional trade networks. We test this hypothesis in Appendix F by interacting our $Treatment_{j,k,t}$ indicators with measures of trade exposure constructed from combining prefectural input-output matrices with firms' pre-existing geographic distribution of assets or employment.

TABLE 4. Bonus Claiming, Investment, and Employment Responses to Technopolis

A. First Stage: Extensive Margin Bonus Depreciation Claims

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.101***	0.087***	0.089***	0.094***	0.070**	0.090***
	(0.032)	(0.034)	(0.032)	(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 purchases			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 purchases is the log gross book value of new PPE excluding buildings, land, and structures, and employment is 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. For the *BJS* estimator, we compute standard errors by taking leave-one-out averages across the cohort treatment effects, which accounts for small cohorts of treated observations and results in more conservative standard errors. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

TABLE 5. Local Spillovers of Technopolis via Untreated Firms

	Bonus claim		Construction		Non-RE purchases		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 purchases is the log gross book value of new PPE excluding buildings, land, and structures, and employment is 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. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

We find no evidence of heterogeneous effects by firms' trade exposure either in terms of imports (supply) or exports (demand).

5.3 Heterogeneous Firm Responses

We now examine heterogeneous responses to the Technopolis policy based on (i) firms' pre-existing physical capital structure, (ii) the extent to which bonus claims have the potential to relieve financing constraints, and (iii) the role of intra-firm transport costs in policy take-up.

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 physical production input shares for each firm. 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.[32] The complete algorithm steps are described in LaPoint (2021), but we provide an outline in Appendix D. 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, recovering the capital input shares relies on two technical 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 Cobb-Douglas, or:

$$f(K_j) = \prod_{i=1}^{6} k_i^{\omega_{i,j}} \quad \text{s.t.} \quad \sum_{i=1}^{6} \omega_{i,j} = 1, \forall j \tag{5.2}$$

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 (5.2). 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 $1980 - 1983$.[33]

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 1-digit industrial sector. For instance, electronics firms with large R&D facilities have a building input share of 0.43, while this is only 0.30 for transportation and 0.33 for retail firms. Although this approach has the advantage of being motivated by theory, 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

[32] The plant-level Census only decomposes tangible assets into land, buildings, machinery, and a residual other category. We also cannot compute other parameters such as the weighted average cost of capital (WACC) and corporate income tax bill which are necessary for the calculations.

[33] 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 (5.2) – we find that YOY investment in long-lived assets falls after the early 1990s crash.

firms; this subsample spans all 1-digit industry codes in the full sample. To overcome this issue, we apply a nearest-neighbor match 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 input 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:

$$y_{j,t} = \gamma_j + \delta_t + \beta_1 \cdot Treatment_{j,t} \times LL - Firm_j \qquad (5.3)$$

$$+ \beta_2 \cdot Treatment_{j,t} \times SL - Firm_j + \eta' \cdot \mathbf{X}_{j,t} + \varepsilon_{j,t}$$

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 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 $\times$ 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.[34] 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.

Table 6 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

[34]This 4% linear rate of depreciation is about double of what Yoshida (2020) finds via an 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 6. Firm-Level Results by Long-Lived Asset Share

	Bonus claim		Construction		Non-RE purchases		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 (5.3) 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 purchases is the log gross book value of new PPE excluding buildings, land, and structures, and employment is 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. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

eligibility. On the other hand, the difference between $\widehat{\beta_1}$ and $\widehat{\beta_2}$ in equation (5.3) 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. 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 0.38 in each subgroup.[35]

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

[35] We also checked whether a simple above/below median split inherent in equation (5.3) is masking non-linear effects across the distribution of ω_{build}. We uncover a U-shaped pattern when we re-estimate versions of (5.3) where we interact $Treatment_{j,t}$ with dummies indicating the quintile of ω_{build}.

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 consider 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:

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

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.[36] In addition to the Hadlock-Pierce index, we also consider 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:

$$y_{j,t} = \gamma_j + \delta_t + \beta_1 \cdot Treatment_{j,t} \times FC_j + \beta_2 \cdot Treatment_{j,t} \times NFC_j + \eta' \cdot \mathbf{X}_{j,t} + \varepsilon_{j,t} \tag{5.4}$$

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 7 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 investment, and 13.7% increase in employment. In contrast, the loading on

[36] 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.

TABLE 7. Firm-level Results by *Ex Ante* Financing Constraints

	Bonus claim		Construction		Non-RE purchases		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 (5.4) 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 purchases is the log gross book value of new PPE excluding buildings, land, and structures, and employment is 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. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

$Treatment \times NFC$ 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 7 suggests financially constrained firms were more likely to claim the cash flow benefit provided by the Technopolis policy. Financially constrained firms then used the funds to finance construction and non-real estate purchases and hire more employees.

5.3.3 Intra-firm Transportation Costs & Policy Take-up

So far we have focused on corporate responses on the intensive margin of policy take-up, meaning conditioning on firms having operations within catchment areas prior to policy implementation. We now relax that assumption by considering how the decision to deploy capital and labor to a location might depend on notions of physical distance to the geographic boundaries of place-based policy eligibility. If the costs of transporting goods or span of control costs associated with employees and managers commuting between locations are substantial, then firms which are more geographically concentrated around major cities rather than the peripheral ones targeted by Technopolis will be less likely to participate.

Examining this question involves extending our baseline difference-in-differences specification in equation (4.1) to a triple differences design like the following:

$$\begin{aligned} y_{j,k,t} = \gamma_j + \delta_t + \beta_1 \cdot \mathit{Distance}_j \times \mathit{Post}_t + \beta_2 \cdot \mathit{Treated}_k \times \mathit{Post}_t \\ + \beta_3 \cdot \mathit{Distance}_j \times \mathit{Treated}_k \times \mathit{Post}_t + \eta' \cdot \mathbf{X_{j,k,t}} + \varepsilon_{j,k,t} \end{aligned} \tag{5.5}$$

where now we have decomposed the $\mathit{Treatment}_{j,k,t}$ dummy previously used into three components. The first component of treatment status, $\mathit{Distance}_j$, is a continuous measure of a firm's physical distance to the Technopolis regions, based on its pre-existing network of plant locations. We offer several ways to compute $\mathit{Distance}_j$ and precisely describe our procedures in Appendix G.5. Essentially, $\mathit{Distance}_j$ captures how close in driving distance the "average" plant of firm j is to the nearest area where deployed capital would be subsidized through special bonus claims. We also explore a semi-parametric version of (5.5) where $\mathit{Distance}_j$ is discretized into bins, rather than assuming that the cost of policy take-up is linear in our notion of distance.

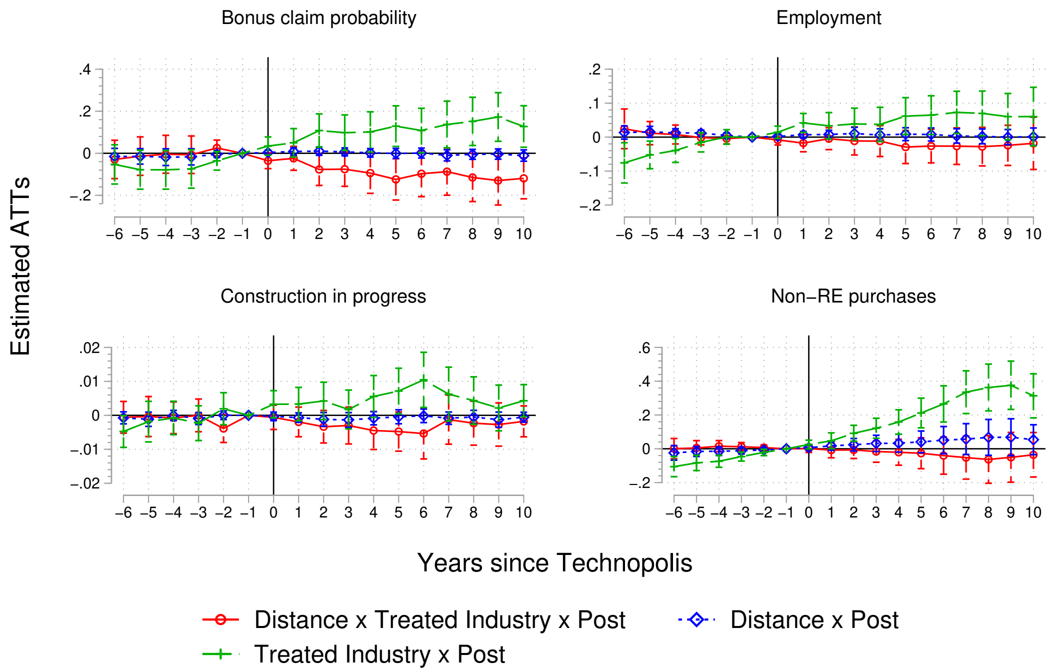
The second component of treatment is whether firm j is classified into one of the 55 4-digit JSIC industries k eligible for Technopolis bonus claims. The final component is an unstaggered policy timing dummy Post_t equal to one in all years after the enactment of the first wave of Technopolis sites in 1984. We adopt a simultaneously absorbing treatment for this model since once we extend the treatment status to the entire firm network it is unclear which Technopolis becomes the pivotal one for determining treatment timing. In other words, there is no well-defined concept of "staggered rollout" with multi-plant firms which can move resources to an entirely new location.[37]

Figure 4 demonstrates how the dynamic treatment effects for our main outcomes in Figure 3 vary by corporate distance to the policy areas. The first stage effect on bonus claim probability (top left panel) is declining with average driving distance to the nearest Technopolis, as shown by the estimates plotted in red. A firm with an average distance 100 km further from Technopolis areas is 10% less likely to claim bonus depreciation. However, there is no appreciable effect of distance on employment or non-real estate CAPX, although the sign of the estimates is always persistently negative. Instead, the $\mathit{Treated}_k \times \mathit{Post}_t$ estimates in green are of a similar trend and magnitude to our main estimates in Figure 3 which define treatment based on existing operations within a Technopolis, while the loadings on $\mathit{Distance}_j \times \mathit{Post}_t$ in blue are roughly constant across time and insignificant for all outcomes.

These patterns point to distance as an important determinant of policy take-up. Yet, among the firms which extract cash flow from the policy, there is no observable difference in the employment or non-real estate investment responses with respect to distance between catchment areas and the internal resource network. This suggests the decision of large firms to respond to local capital investment subsidies depends on threshold fixed costs of opening a new plant which is potentially

[37]Still, we try staggered versions of (5.5) with $\mathit{Post}_{j,t}$ set to unity in years after the rollout of the Technopolis site closest to all plants within the firm's network and find virtually identical results.

FIGURE 4. Triple Differences: Policy Take-Up as a Function of Driving Distance



Notes: Each panel shows the response of an outcome of interest estimated from a dynamic version of the unstaggered triple differences model of (5.5) via OLS. We plot the loadings on the triple difference $Distance_j \times Treated_k \times Post_t$ in red, those on $Distance_j \times Post_t$ in blue, and $Treated_k \times Post_t$ in green. 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. All dynamic effects are relative to one year before Technopolis eligibility begins. We use an equal-weighted average measure of distance to the nearest Technopolis across plants within each firm (see Appendix G.5 for details). We rescaled estimates with $Distance_j$ so that the effect is in terms of a 100 km increase in distance. The bars show 95% confidence intervals obtained from standard errors clustered at the firm level.

on the outskirts of the existing network of locations. Hence, local capital lock-in provisions, like those of U.S. Opportunity Zones, are a double-edged sword. Tying the subsidy to local deployment helps bring resources to peripheral economies, but it also particularly increases the cost of take-up for firms in high-productivity areas with which those economies are struggling to compete.

5.4 Firms' Internal Labor & Capital Market Responses

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 *yūhō* 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 j operates 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 from the DBJ database and 1986–2000 from COM – are located in a Technopolis eligible area.[38] The number of manufacturing plants in our sample grows from 3,470 in 1980 (from the *yūhō*) 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 6, the responses we document in our staggered DD models are driven by firms with a larger share of long-lived assets in production. We should thus 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 and job creation in areas not targeted by policymakers.

Figure 5 provides visual evidence in favor of the narrative that ineligible areas captured much of the jobs intended for plants in eligible areas. We subset our data to parent firms in a 4-digit industry eligible for Technopolis bonuses who report strictly positive bonus claims during the policy regime and who have a plant presence in both Technopolis and non-Technopolis cities. Figure 5 separately computes the change in the total number of eligible (blue) and ineligible plants (red) and plots these changes in plants (Panel A) or employment growth (Panel B) against ω_{build}, which can vary between 0 and 1. Therefore, each eligible parent firm will appear twice on the plot. We compute growth over 1980 and 1995 to allow all Technopolis locations to become eligible – recall the last site was designated in 1989 – and to allow construction projects begun during the initial Technopolis period to be completed.[39]

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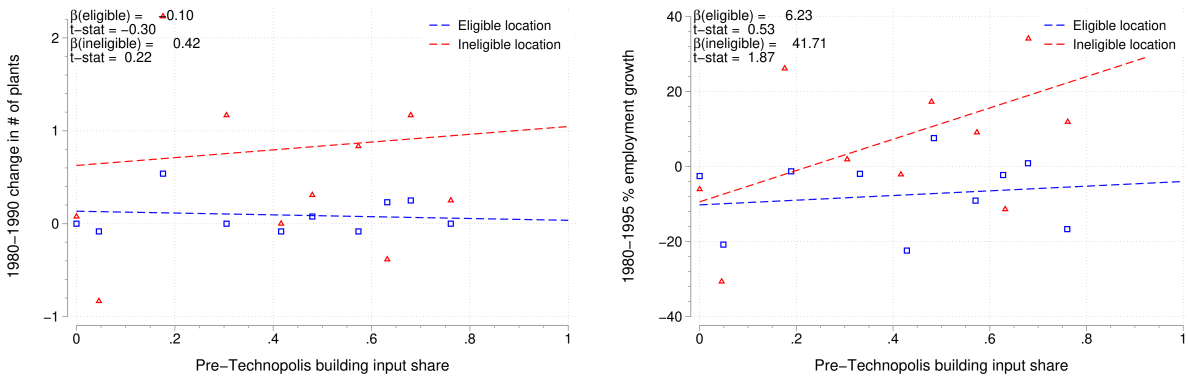
[38] Under a more stringent definition of $Treatment_{i,j,k,t}$ where in step (ii) we consider the plant treated at the industry level based on the 4-digit industry code attached to the plant rather than the parent firm, we find only 3.4% of plants in the COM sample are eligible. Since the depreciation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

[39] Based on construction itemizations hand-collected from the 1980 *yūhō* 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. The Technopolis policy also concluded in 1995, as the bonus rate phased out according to Table 1.

FIGURE 5. Firm Expansion in Policy Eligible vs. Ineligible Areas

A. Growth in Number of Plants by ω_{build} B. Employment Growth by ω_{build}



Notes: In each panel a point on the graph corresponds to a bin of DBJ firms in a Technopolis-eligible industry 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 bins in the 1980–1995 change in the number of plants (Panel A) or employment growth (Panel B) 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 will appear twice on the plot. Following the optimal binning criteria of Cattaneo et al. (2023), for each set of points we bin into deciles while using all the data to fit a least-squares line where observations are weighted by the parent firm's balance sheet size in 1980. We winsorize employment growth at the 99th percentile to ensure robustness to outliers. The x-axis variable is the firm-level building input share ω_{build} computed via the methods outlined in Section 5.3 and described in detail in Appendix D. We show how ω_{build} is proportional to the subsidy rate in Appendix C. t-stats computed using heteroskedasticity-robust standard errors.

At the extensive margin of investment in Figure 5 we observe that there is a small, negative gradient (slope $= -0.10$) in the change in the number of plants and ω_{build} for eligible areas, and a small positive gradient for ineligible areas (slope $= 0.42$); in both cases, the gradient is statistically insignificant, and there is no statistically significant difference between the two slopes (p-value $=$ 0.99). The lack of any discernible relationship between new plant creation and the subsidy rate 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 growth in Panel B of Figure 5, there is a clear divergence between eligible and ineligible areas. For employment growth rates the gradient is 6.23 in eligible areas, and 41.71 in ineligible areas; the difference in the unweighted slopes is marginally statistically significant (p-value $= 0.09$). We lose statistical power in examining this leakage outcome due to the relatively small number of multi-plant firms ($N = 166$) who both take up the policy and have resources spanning eligible and ineligible locations. We can translate these slopes to semi-elasticities with respect to changes in the physical capital subsidy rate. We describe the relevant accounting identities in Appendix C and show that the subsidy rate implied by bonus depreciation is linear in the firm's long-lived capital (i.e. building) input share. An $\omega_{build} = 0$ corresponds to an average subsidy rate of 0.9%, while $\omega_{build} = 1$ implies an average subsidy rate of 3.6%. For plants in eligible areas the employment semi-elasticity is a statistically insignificant $6.2/(3.6\% - 0.9\%) = 2.3$, while for plants outside Technopolis it is $41.7/(3.6\% - 0.9\%) = 15.4$. Hence, employment within eligible firms is almost seven times more responsive in untreated areas.[40]

Several different strategies at the parent firm level could be driving this divergence in net job creation between plants in areas eligible vs. ineligible for physical capital subsidies. For instance, it could be that while, on net, hiring at ineligible plants outstripped that in eligible plants, firms were less likely to layoff employees in eligible plants. Since output at eligible plants may have been more exposed to local negative demand shocks due to the macroeconomic downturn that began at the end of the 1980s, in such a scenario Technopolis might have acted as a "shock absorber," or as a subsidy for labor hoarding in the relatively high labor productivity but ineligible areas (Fay & Medoff 1985; Biddle 2014). This labor hoarding story offers one possible rationalization for why 101 of the 166 firms operating in Technopolis areas who claimed bonuses experienced zero growth in Technopolis area employment over 1980–1995.

In Table 8, we decompose Panel B of Figure 5 into job creation and destruction decisions for eligible vs. ineligible areas. To do so, we estimate difference-in-differences specifications for hiring or firing outcomes $\mathbb{1}\{\Delta L \lesseqgtr 0\}$ of the following form:

$$\begin{aligned} \mathbb{1}\{\Delta L \lesseqgtr 0\}_{g,j,k} &= \alpha + \beta_1 \cdot Treatment_{j,k} + \beta_2 \cdot Takeup_{j,k} \\ &+ \beta_3 \cdot Treatment_{j,k} \times Takeup_{j,k} + \eta' \cdot \mathbf{X}_{j,k} + \varepsilon_{g,j,k} \end{aligned} \tag{5.6}$$

wher $g \in \{T, NT\}$ indexes whether employment changes ΔL occur in Technopolis (T) or non-Technopolis (NT) areas. $Treatment_{j,k} = 1$ if the parent firm j is in a 4-digit industry k which is eligible for Technopolis bonuses. $Takeup_{j,k}$ is a dummy equal to unity if the firm reports strictly positive cash flows from bonus depreciation claims during the policy regime. In columns (4) and (8) of each panel in Table 8, we adopt a more stringent definition of $Takeup$ which requires firms to have $\omega_{build} > 0$ in addition to reporting bonuses. This additional restriction on which firms count as "treated" incorporates the fact that firms relying on physical space as a production input can earn the highest subsidies, as indicated by the reduced form effects plotted in Figure 5 and the bonus depreciation rates in Table 1.[41]

The vector of controls $\mathbf{X}_{j,k}$ includes 1-digit sector fixed effects (i.e. light, heavy, and electronics manufacturing) and quantiles for initial size and age, motivated by our evidence in Section 5.3 that smaller and younger firms benefit more from the immediate cash flows obtained via bonus claims. We add in initial financial controls in the form of Tobin's Q, EBITDA, and OCF. Equation (5.6)

[40] This calculation assumes that firms would normally elect to use the declining balance depreciation method for physical assets in the absence of bonus depreciation. We show in Appendix C that the declining balance method strictly dominates straight-line (linear) depreciation, given the physical capital input shares we calculate for the large firms in our sample in Appendix D. The x-axis subsidy rate instead varies between 1.4% and 4.4% if we assume firms prefer linear depreciation.

[41] We report the more conservative heteroskedasticity-robust standard errors rather than clustering at the 4-digit industry level. Clustering at the 2-digit industry level results in too few clusters for standard errors to be consistently estimated (Angrist & Pischke 2009, Ch. 8).

TABLE 8. Hiring and Firing Decisions of Firms Claiming Subsidies

A. Hiring and Firing in Technopolis-Eligible Plants

	Hiring $\mathbb{1}\{\Delta L > 0\}$				Firing $\mathbb{1}\{\Delta L < 0\}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.042	0.035	0.052	0.035	-0.096^{***}	-0.076^{**}	-0.071^{**}	-0.081^{**}
	(0.040)	(0.041)	(0.041)	(0.043)	(0.032)	(0.031)	(0.031)	(0.033)
Takeup	0.133^{***}	0.136^{***}	0.089^{**}	0.051	0.017	0.015	−0.039	−0.048
	(0.044)	(0.044)	(0.044)	(0.047)	(0.039)	(0.039)	(0.040)	(0.044)
Treatment × *Takeup*	-0.143^{**}	-0.151^{**}	-0.154^{**}	-0.134^{**}	−0.001	0.005	0.026	0.055
	(0.064)	(0.064)	(0.063)	(0.067)	(0.050)	(0.051)	(0.051)	(0.057)
1-digit sector FEs		✓	✓	✓		✓	✓	✓
Size & age bins			✓	✓			✓	✓
Financial controls			✓	✓			✓	✓
Exclude if $\omega_{build} = 0$				✓				✓
# Firms	740	740	729	627	740	740	729	627
Adj. R^2	0.010	0.009	0.072	0.059	0.015	0.024	0.070	0.075

B. Hiring and Firing in Ineligible Plants

	Hiring $\mathbb{1}\{\Delta L > 0\}$				Firing $\mathbb{1}\{\Delta L < 0\}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.015	−0.018	−0.018	−0.039	−0.015	0.018	0.019	0.039
	(0.049)	(0.049)	(0.049)	(0.052)	(0.049)	(0.049)	(0.049)	(0.052)
Takeup	0.002	0.004	0.001	−0.056	−0.007	−0.010	−0.008	0.048
	(0.050)	(0.050)	(0.052)	(0.055)	(0.050)	(0.050)	(0.052)	(0.056)
Treatment × *Takeup*	0.161^{**}	0.150^{**}	0.165^{**}	0.225^{***}	-0.155^{**}	-0.144^{*}	-0.159^{**}	-0.217^{***}
	(0.074)	(0.074)	(0.075)	(0.081)	(0.074)	(0.074)	(0.075)	(0.081)
1-digit sector FEs		✓	✓	✓		✓	✓	✓
Size & age bins			✓	✓			✓	✓
Financial controls			✓	✓			✓	✓
Exclude if $\omega_{build} = 0$				✓				✓
# Firms	740	740	729	627	740	740	729	627
Adj. R^2	0.015	0.028	0.052	0.062	0.014	0.027	0.052	0.062

Notes: The table reports results from estimating specification in equation (5.6) separately for hiring in Technopolis-eligible plants (Panel A, columns 1–4), firing in Technopolis-eligible plants (Panel A, columns 5–8), hiring in Technopolis-ineligible plants (Panel B, columns 1–4), and firing in Technopolis-ineligible plants (Panel B, columns 5–8). We compute hiring and firing dummies using employment growth ΔL between 1980 and 1990. In all columns, we subset to the set of multi-plant manufacturing firms in DBJ which can be matched between our sample with hand-collected information on employment by location from 10-Ks in 1980 and comparable employment statistics from COM in 1990. 1-digit sector fixed effects consists of dummies for whether the firm's primary 1-digit JSIC is in light, heavy, or electronics manufacturing. Size & age bins are quantiles of firm assets and age as of 1980. Financial controls refer to the value of Tobin's Q, EBITDA, and OCF as of 1980. See Appendix G.2 for definitions of these accounting measures. In columns (4) and (8) of each subtable, we restrict to firms with strictly positive building input shares ω_{build} in their production function, where we compute ω_{build} using the steps outlined in Section 5.3 and the perpetual inventory method described in Appendix D. Heteroskedasticity-robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

therefore compares two manufacturing firms with similar starting size, age, valuation, and income who claim bonus depreciation during the policy period, except one firm specializes in products which qualifies it for the more generous bonus rates offered by the Technopolis policy.

Our results in Table 8 suggest that Technopolis did not act as a shock absorber on the extensive margin of employment. Firms were not more or less likely to layoff Technopolis area workers if they claimed bonus subsidies under the policy (Panel A). Rather, Technopolis seems to have subsidized firms' hoarding of labor in ineligible areas on the eve of the recession (Panel B). Indeed, if we rerun the specification using a longer time window extending into the Lost Decade of the 1990s, this attenuates the results on both hiring and firing in ineligible areas, suggesting corporate employment strategies were driven by precautionary motives. That hiring in ineligible areas is concentrated during the early part of the policy regime is consistent with the kink point in the bonus rate schedule at five years since Technopolis creation (Table 1). These effects are economically large; manufacturing firms are 13 to 15 p.p. less likely to hire in eligible areas, and 15 to 23 p.p. more likely to hire in ineligible areas. Consistent with the subsidy rate being proportional to ω_{build}, the results are more pronounced when we restrict to firms with buildings in their production function.

What do we know about jobs created in ineligible areas under Technopolis? Firms only report jobs located at a manufacturing site in responding to the Census of Manufactures (COM) survey. To render the employment numbers in COM comparable to jobs reported on firms' annual 10-Ks from the earlier period, we restrict to employment at sites with either a factory or both a branch office and the HQ. This means that non-manufacturing jobs would only be included in our measure of ΔL if they are located at the firm's HQ site which also houses a branch office.[42]

We isolate HQ employment that could possibly include non-manufacturing roles for cases where the HQ is not located in a Technopolis and re-estimate equation (5.6), focusing on changes in this measure of HQ employment.[43] We find no effects on hiring or firing when we hone in on ineligible HQ employment; for instance, the point estimate on the coefficient for hiring corresponding to the full set of controls in column 4 of Table 8 is a statistically insignificant 0.079 (p-value = 0.23). Hence, this increased propensity to hire within ineligible locations of the firm points to rebalancing labor from low to high productivity areas rather than reoptimization across different types of labor skills within the firm.

Taken together, it appears 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 towards pre-existing plants in ineligible areas. The possibility of this "leakage" of public funds was noted by Broadbent (1989), who conducted onsite qualitative surveys of newly established robotized facilities – including those of several companies in our dataset (e.g. Sony and Canon) –

[42]The COM survey sheets for pre-2000 survey waves are here (in Japanese): https://d-infra.ier.hit-u.ac.jp/Japanese/census-survey/b005.html. The survey questions pertaining to how firms report employees are identical from 1980 to 2000, which covers our sample period.

[43]Only 18 firms in our sample have their HQ located in a Technopolis site.

during the early years of the Technopolis program. Thus, while the place-based tax incentives promoted irreversible investment in areas outside the major metros, it is unlikely that these investments directly benefited *local* labor markets in the targeted areas. Leakage may or may not be desirable from an overall welfare perspective, since subsidizing lower marginal productivity areas can generate aggregate losses by limiting agglomeration externalities (Gaubert 2018). Firms mitigate the paternalistic spatial misallocation inherent in place-based policies by redistributing income from corporate subsidies to plants with higher marginal productivities of labor.

6 Reduced Form Welfare Analysis

Concerns about Okun's "leaky bucket" notwithstanding, by how much did Technopolis improve welfare, if it did at all? Our approach to answering this question builds on the procedures outlined in Busso, Gregory, & Kline (2013), who assess the incidence of U.S. Empowerment Zones, Chaurey (2017) on regional tax exemptions for businesses in India, and Lu, Wang, & Zhu (2019), who examine local gains from corporate income tax cuts in China's special economic zones (SEZs). To start, we divide up total surplus into three components: worker surplus, producer surplus, and corporate income tax revenue. To the extent that Technopolis created positive spillovers to the wealth of local property owners or local enterprise tax receipts, this division will produce lower-bound estimates of the welfare gains from the policy.

We measure worker surplus as total wage and non-wage compensation. For producer surplus, we compute after-tax corporate profits from our balance sheet data as net income before depreciation, after taxes paid. Revenues are corporate taxable income times the prevailing national corporate income tax rate. We use this accounting-based definition of revenues rather than observed taxes paid, because the latter is a function of previous tax bills through firms' decisions to file late or carry forward net operating losses. Importantly, our use of balance sheet data allows us to net out taxes from profits, so we do not inadvertently double count the surplus generated by tax revenues.

We then rerun our baseline difference-in-differences (DD) regression in (4.1) for each of these three surplus measures as the outcome, with results reported in Table 8. We estimate Technopolis increased workers' compensation by 6.3%, corporate profits by 2.5%, and taxable income by 13.2% (using $\exp(\widehat{\beta})-1$ to transform the coefficients), even conditional on including size, age, HQ region, and main bank-by-year fixed effects. Our estimated coefficients can then be used to scale down actual wages w, corporate profits π, and tax revenues $\tau \cdot \gamma$, and recover the welfare gain from each surplus piece by taking the difference between the actual and counterfactual flows:

$$\Delta w = w - \widetilde{w} = w \cdot \widehat{\beta}^{wages}/(1+\widehat{\beta}^{wages}) \tag{6.1}$$

$$\Delta \pi = \pi - \widetilde{\pi} = \pi \cdot \widehat{\beta}^{profits}/(1+\widehat{\beta}^{profits}) \tag{6.2}$$

$$\tau\Delta\gamma = \tau \cdot (\gamma - \widetilde{\gamma}) = \tau \cdot \gamma \cdot \widehat{\beta}^{base}/(1+\widehat{\beta}^{base}) \tag{6.3}$$

TABLE 9. Technopolis Effects on Surpluses and Tax Base

	Wage bill		Corporate profits		Taxable income	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.061**	0.063**	0.025***	0.027***	0.124*	0.113*
	(0.028)	(0.029)	(0.008)	(0.008)	(0.070)	(0.068)
Estimator	OLS	*BJS*	OLS	*BJS*	OLS	*BJS*
Firm FEs	✓	✓	✓	✓	✓	✓
Controls × year FEs	✓	✓	✓	✓	✓	✓
N	27,567	27,567	28,941	28,941	27,462	27,462
# Firms	1,374	1,374	1,406	1,406	1,506	1,506
Adj. R^2	0.952	0.952	0.613	0.613	0.585	0.585

Notes: The table provides the results from estimating our pooled baseline specification in equation (4.1) via either OLS (odd columns) or the estimator of Borusyak, Jaravel, & Spiess (2023) (odd columns). The wage bill is defined as the log of the sum of wage and non-wage compensation which includes employer retirement contributions and pensions. Corporate profits is net income before depreciation after taxes, deflated by its firm value at the beginning of the panel. Taxable income is the sum total of all gains less allowable losses, left-censored at zero and transformed using the IHS function to accommodate firm-years with no taxable income. All regressions include as controls dummies for size quintile (by total assets), quintile of age measured from the Tokyo Stock Exchange listing date, Census region of the HQ, and main bank, all interacted with a full set of year dummies. Standard errors clustered at the firm level are in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

where τ is the corporate income tax rate, γ is taxable income, and tilde indicates counterfactual values.[44] We obtain nearly identical PDV benefit amounts if we estimate dynamic versions of (6.1)–(6.3) and scale down the actual flows year by year.

When we use our DD estimates in Table 8 to calculate the counterfactual flows, as in the above series of equations, we find that Technopolis entailed a welfare gain of \$56.72 billion in real PDV terms at a 7% discount rate (or, \$66.03 billion discounted at 5%), as shown in Table 9. This PDV surplus amounts to roughly 40% of one year's worth of average annual profits among listed firms.[45] We illustrate with a diagram of the labor market in Figure 6 the empirically relevant case where all three pieces of the pie increase in response to a physical capital subsidy which lowers the effective corporate income tax rate to $\tau' < \tau$, resulting in an outward shift in the labor demand curve and shrinkage in the deadweight loss (pictured as the red triangle) from the distortion of corporate income taxes on real wages.[46]

[44]We measure taxable income for each firm as taxes paid plus net income before depreciation. We describe the historical corporate income tax rate schedule in Appendix H.2.

[45]The total surplus is large relative to total counterfactual income tax revenues collected from corporate firms over the 12-year period and is equivalent to 1.02% of real 1995 Japanese GDP.

[46]Since we uncover no evidence of spillovers across the corporate sector in Section 5.2, we assume in the diagram that the labor supply curve does not shift.

TABLE 10. Reduced Form Estimates of Welfare Gains from Technopolis

	Actual value	$\widehat{\beta}$	Counterfactual value	Benefits
Wage bill	941.98	0.063	886.24	55.74
Corporate profits	605.34	0.025	590.46	14.88
Tax revenue	162.72	0.132	143.74	18.98
Total surplus	1,710.04	–	1,620.44	89.60
PDV total ($r = 5\%$)	1,256.53	–	1,190.50	66.03
PDV total ($r = 7\%$)	1,077.60	–	1,020.88	56.72

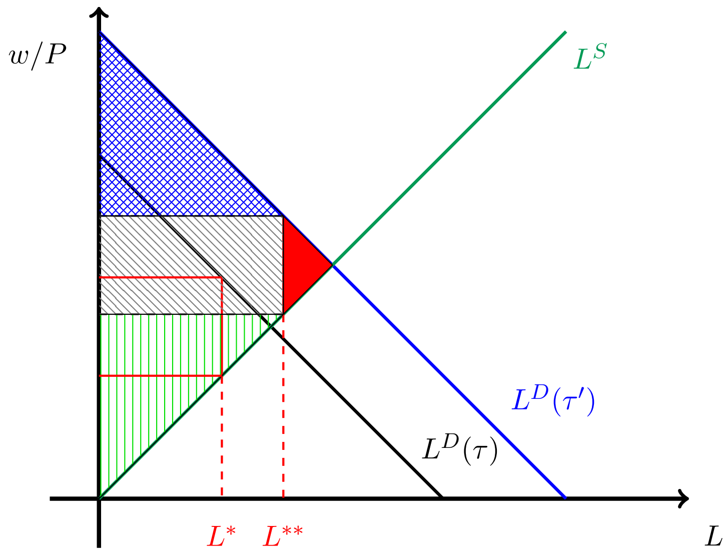
Notes: The table breaks down the benefits of the Technopolis policy accruing to workers, firms, and the government in billions of real 2010 USD. The last two rows report the PDV totals of the worker, producer, and government surpluses at a 5% or 7% discount rate, which matches our cost-per-job discounting assumptions (see Appendix H); the other rows report the undiscounted cash flow totals. For tax revenues, we take annual total taxable income in each year and multiply it by the prevailing corporate income tax rate, rather than using taxes paid, to create a surplus measure that is invariant to firms' intertemporal shifting of tax bills via carryforward losses and late filings. To convert annual cash flows from nominal JPY to real USD, we apply the historical exchange rates from the University of British Columbia Pacific Exchange Rate Service (available at `https://fx.sauder.ubc.ca/`) and then convert to real USD using the all items U.S. CPI-U.

In Figure 7 we decompose how the real net present value cash flow benefits accrue throughout the policy regime for each surplus category. Panel A shows that actual corporate profits rapidly grow in the first few years of Technopolis. However, turning to the net benefit flows in Panel B, corporate profits account for only 15% of the overall welfare gain as of the last year of the policy in 1995. Instead, total compensation (i.e. worker surplus) accounts for the bulk of the gains from Technopolis. The benefits are quantitatively similar if we instead exclude non-wage compensation from our definition of the wage bill: 58.6% vs. 61.7% of total generated surplus for wages vs. total compensation, respectively.

That most of the gains from the bonus depreciation scheme accrue to labor in the form of higher wages is consistent with evidence from Fuest, Peichl, & Sigeloch (2018) on the pass through of corporate income taxes in Germany, which has similar tax laws to Japan. The incidence of the corporate tax subsidy on labor implies that the welfare gains arise, in part, from the leakage response of multi-plant firms. Aggregate TFP is much higher when firms allocate resources to set marginal products equal across plants (Hsieh & Klenow 2009), and PBPs like Technopolis create efficiency "wedges" by subsidizing lower marginal productivity areas, as proxied by value added per capita (see Appendix A.3). Our focus on corporate firms means that our welfare estimates do not capitalize the direct effects to eligible private firms or spillovers to ineligible private firms, both of which are more likely to have only one plant. Using the aggregate COM data in Section 5.1, we obtain $\widehat{\beta}^{wages} = 0.143$, suggesting the pass through to labor markets is larger for private firms.

Another common metric for evaluating place-based policies in the literature is "cost per job," or lost tax revenues implied by the subsidy rate scaled by the number of net jobs created. Cost per

FIGURE 6. Graphical Depiction of Welfare Gains from Technopolis



Notes: The figure illustrates the impact on the labor market of providing firms subsidies through Technopolis bonus depreciation. Here, bonus depreciation is represented by a lowering of the corporate income tax rate from τ to $\tau' < \tau$. Consistent with our reduced form results in Section 5, the labor demand curve shifts out, resulting in job creation represented by $(L^{**} - L^{*})$, and a new deadweight loss from taxation represented by the shaded red triangle. As we conclude in our empirical welfare analysis, the corporate surplus (blue), the worker surplus (green), and tax base (gray) all grow relative to the pre-reform period. We model the labor supply curve as fixed in this example, given the lack of evidence of spillovers. For exposition, this figure also assumes the incidence of the corporate income tax is borne by workers via pass through to real wages, which in practice can occur either through firms lowering wages or increasing consumer goods prices in response to higher tax rates.

job is a partial equilibrium measure that does not take into account growth in the tax base due to changes in corporate profits, which Figure 7 shows is a quantitatively important force in the case of Technopolis. In Appendix H, we describe the procedures we use to arrive at a cost-per-job estimate from Technopolis of $15,714. Our cost-per-job estimates sit at the low end among those computed in studies of place-based investment subsidies. Fixed hiring costs for specialized labor are likely lower in major cities with thicker labor markets, such as the Technopolis-ineligible sites where hiring occurs (as shown in Table 8) than in Technopolis sites (Di Addario 2011).[47]

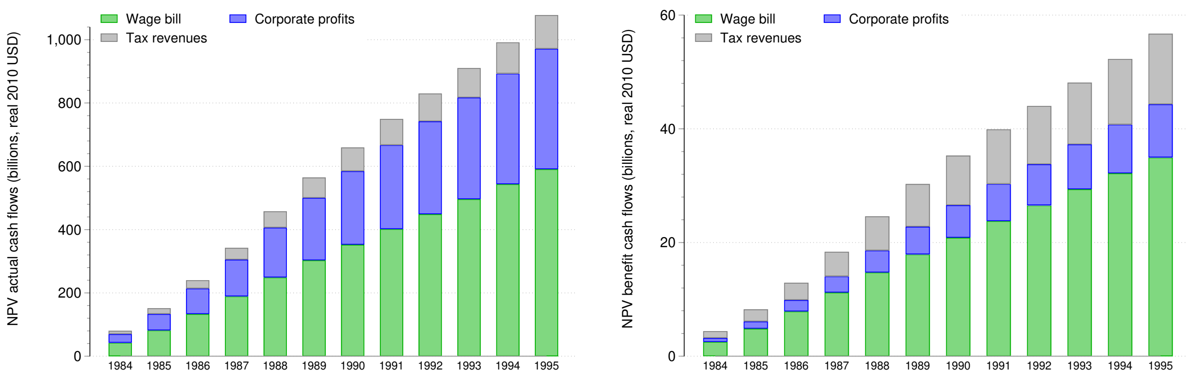
7 Conclusion

We investigate the effects of spatially targeted tax incentives on the geography of corporate resource allocation using a series of national 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 spatial distribution of corporate resources

[47] Evidence in the modern labor literature largely rejects the hypothesis that fixed costs of hiring are, on average, large (Kramarz & Michaud 2010; Blatter, Muehlemann, & Schenker 2012). An economies of scale story in hiring for corporate firms is unlikely to explain our relatively low cost-per-job numbers.

FIGURE 7. Actual and Net Benefit Cash Flows over the Technopolis Regime

A. Actual Cash Flows B. Benefit = Actual − Counterfactual



Notes: Panel A displays the actual NPV cash flows for the wage bill, after-tax corporate profits, and tax revenues. Panel B displays the implied policy benefit, derived from taking the difference between the actual and counterfactual flows in each year. We use a discount rate of $r = 7\%$ to match what we use in our baseline cost-per-job analysis (Appendix H). A real discount rate of 7% is comparable to the average observed daily rate on the 1-year JGB of 6.4% during the first year of the policy.

and the composition of inputs used in production – plays in the targeting vs. retention trade-off in place-based policies. We find that eligible 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.

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 using long-lived capital inputs. Another important distinction of the bonus depreciation schedule offered by Japan's Technopolis policy is that it 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. Bonus depreciation as a place-based policy promotes 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, our results cast doubt on the ability of place-based incentives extended to large multi-plant firms to stimulate peripheral labor markets. While firm-level employment increased by around 7% after 10 years of the new policy regime, hiring on the margin of capital subsidization occurred at sites where physical investment was not eligible for bonus claims. Our key takeaway is that local capital subsidies may fail to mitigate regional inequality but can result in net gains for the aggregate economy. This is because large firms take advantage of subsidies by investing capital in eligible areas, but then use the proceeds to hire in ineligible areas, undoing the spatial misallocation of funds inherent in regional industrial policy. Given the parallels between Technopolis and local incentives built into the U.S. CHIPS and Science Act of 2022, our study has important implications for the long-run viability of ongoing high-tech industrial policy initiatives.

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Online Appendix to

Place-Based Policies and the Geography of Corporate Investment

by Cameron LaPoint (Yale SOM) and Shogo Sakabe (LMU Munich)

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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 Equipment	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 municipal 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).

A.3 Historical Narrative of 1980s Japanese Industrial Policy

In this section we offer more details from government reports and narrative studies on how the Ministry of International Trade and Industry (MITI) selected cities and industrial sectors for inclusion in the Technopolis program. We document that Technopolis areas had *ex ante* greater manufacturing sector employment and value-added per worker (MPL), but lower value-added per machine (MPK), which underpinned the decision of the government to offer subsidies for physical capital rather than for labor. Compared to the unsubsidized major metro areas, the regional hub cities within each Technopolis feature lower productivities of both labor and capital.

A.3.1 Technopolis Site and Industry Selection Process

A.3.2 Economic Conditions in Technopolis Sites

Consistent with the selection criteria, Table A.3 shows that Technopolis policy sites have more manufacturing employment and establishments, with a larger tangible capital stock than their ineligible counterparts. While eligible areas are more populated on average than ineligible locations, they have much lower population density and slightly lower per capita income. Both groups of areas have similar baseline unemployment rates and government spending ratios, with most municipalities running a very close to balanced budget during this period. The main discrepancy 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. 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.[1]

Figure A.1 uses the public data from the Census of Manufactures (COM) to map the distribution of real per capita value added across Japanese municipalities on the eve of the Technopolis program in 1983. For production functions which are constant returns to scale in labor and physical capital, value added per worker Y/L is proportional to the marginal product of labor (MPL), and value added per machine Y/K is proportional to the marginal product of capital (MPK). The blue polygons indicate the collections of municipalities enumerated in Appendix A.2 which were eventually selected to be a Technopolis site. The *ex ante* MPL is 13% greater, on average, in Technopolis cities than in non-Technopolis cities. However, the reverse is true for the MPK; value-added per machine was, on average, 33% lower in Technopolis cities. However, if we compare the set of regional hub cities within each Technopolis to the largest metro areas, where the majority of multi-plant firms host their HQ, subsidized areas were less productive on both the labor and capital side; the MPL is 25% lower in Technopolis hubs, and the MPK is 8% lower.[2]

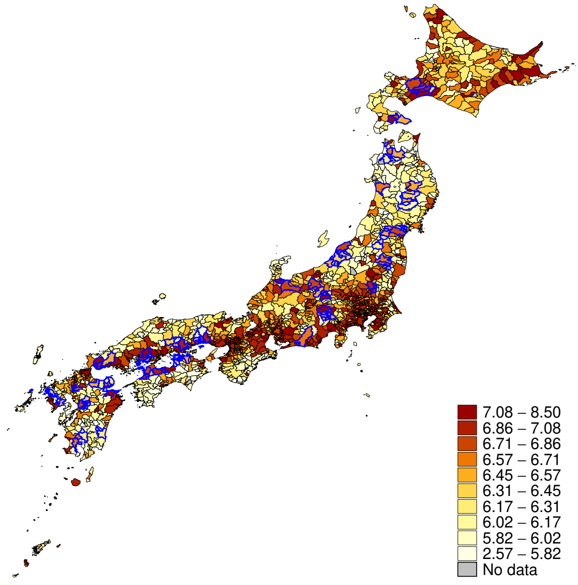
Did Technopolis help the less productive, subsidized, areas "catch up" to the rest of the country in terms of per capita value added, employment, and production capacity? We examine this possibility in Figure A.2, in which we plot for each variable its log level on the x-axis and its growth rate beyond

[1] The differences in local macroeconomic conditions are similar to those in Table A.3 when we instead compare areas eligible to those ineligible under the later Intelligent Location policy. See Appendix B for a list of industries and areas eligible for bonus depreciation under Intelligent Location.

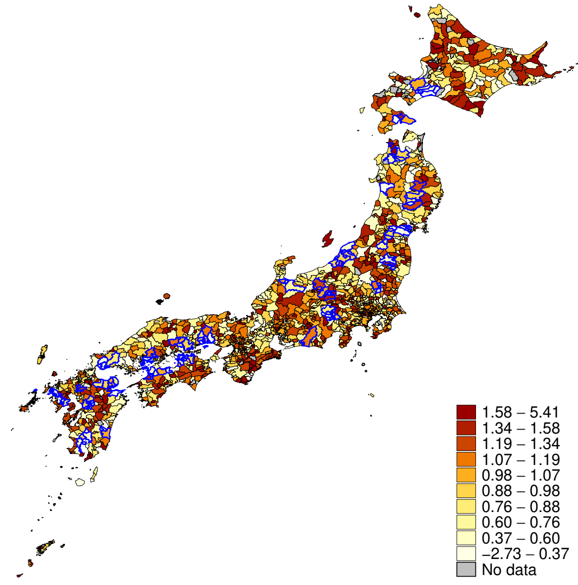
[2] In this calculation, the largest metro areas correspond to "designated city" (population $>$ 500,000) classified by the Japanese government which were not also named as a Technopolis city.

FIGURE A.1. Map of Pre-Technopolis (1983) Manufacturing Productivity

A. Real Value Added Per Worker: $\log(Y/L)$



B. Real Value Added Per Machine: $\log(Y/K)$



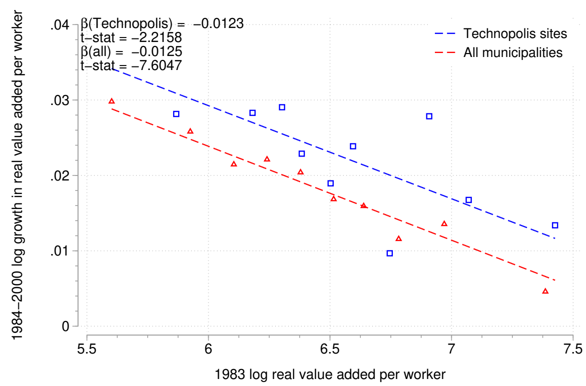
Notes: In each map, we highlight Technopolis sites in polygons outlined in blue. Panel A plots the distribution of log real value added per worker L, or $\log(Y/L)$, which is a proxy for firms' marginal product of labor. Panel B instead shows the distribution of log real value added per machine, or $\log(Y/K)$, a proxy for firms' marginal product of capital. The denominator in Panel B is properties, plants, and equipment (PPE) measured in book value in yen. To obtain these local manufacturing productivity measures, we take the sum of Y, K, and L across all 2-digit manufacturing sectors within the same municipality and year. Each map sorts municipalities into deciles of per capita value added. We obtain Y, K, and L from the public-use data files from the METI Census of Manufactures (COM). We impose modern municipal boundaries using the historical city code crosswalk available through RIETI (Kondo 2019), and exclude 9 municipalities which merged with another municipality during the last available Census year of 2015.

the policy regime (1984–2000) on the y-axis.[3] Downward sloping lines indicate regional convergence for each measure, as this means cities with greater log levels experienced more muted growth. The industrial policy did help the less productive Technopolis sites "catch up" to the more productive Technopolis sites in terms of employment, as evidenced by the blue lines. But there is little evidence that the Technopolis areas caught up to the non-Technopolis areas, which was a goal of the policy and part of the "good jobs" objective promoted by the U.S. CHIPS Act. First, for real value added per worker, we note that the slope of the convergence lines is statistically identical between Technopolis vs. all cities, so that convergence occurring in the post-reform period appears to be due to factors unrelated to the industrial policy itself. Second, convergence in employment and net plant creation is far less pronounced across regions rather than within Technopolis regions (Panels C and D, respectively). Convergence is 6.1 times stronger for manufacturing employment within Technopolis regions than across all regions. Instead, our results in Section 5.4 show that firms concentrated their manufacturing hiring in the larger, more productive cities within their network of existing plants.

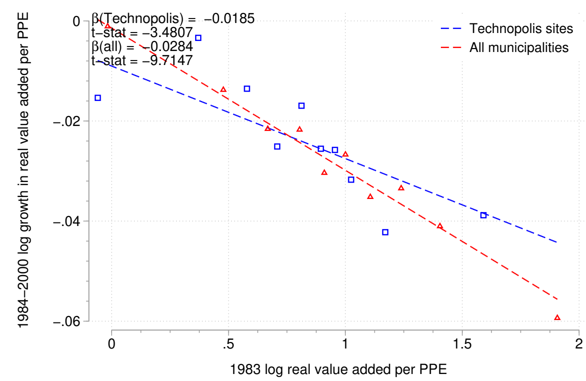
[3]The convergence patterns in Figure A.2 are almost identical if we calculate growth rates only up until the last year of bonus eligibility (1994), as stipulated in Table 1.

FIGURE A.2. Post-Technopolis Convergence in Regional Manufacturing Outcomes

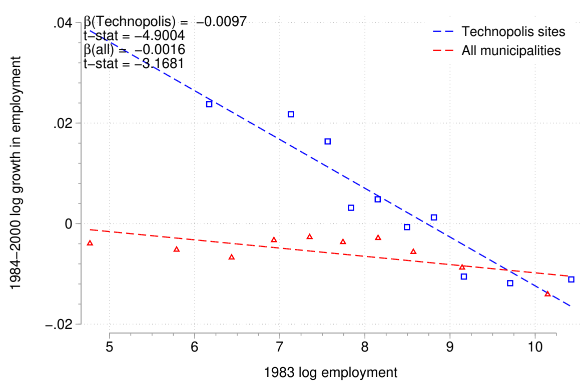
A. Real Value Added Per Worker: $\log(Y/L)$



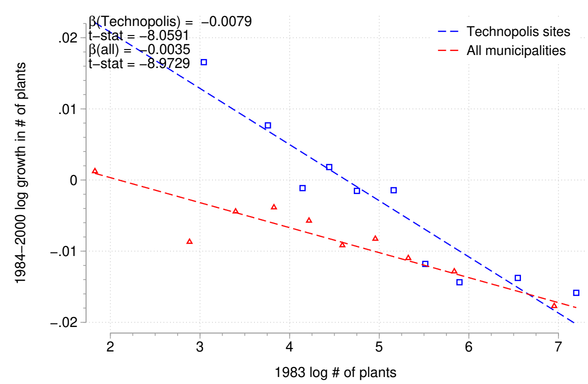
B. Real Value Added Per Machine: $\log(Y/K)$



C. Manufacturing Employment: L



D. Number of Manufacturing Plants N



Notes: The figure shows regional convergence in various manufacturing sector outcomes by plotting the cross-sectional relationship of post-Technopolis growth against pre-Technopolis log levels of the same outcome variable. In each panel, points in red represent bins over all municipalities. Points in blue represent the same statistics except computed over only Technopolis-eligible municipalities. For each set of points we bin into deciles while using all the data to fit a least-squares line. Panel A performs this exercise for log real value added per worker L, or $\log(Y/L)$, which is a proxy for firms' marginal product of labor. Panel B instead uses log real value added per machine, or $\log(Y/K)$, a proxy for firms' marginal product of capital. The denominator in Panel B is properties, plants, and equipment (PPE) measured in book value in yen. Panel C examines manufacturing employment, while Panel D examines the number of manufacturing plants N. To obtain these local manufacturing outcome measures, we take the sum of Y, K, L, and N across all 2-digit manufacturing sectors within the same municipality and year. We obtain Y, K, L, and N from the public-use data files from the METI Census of Manufactures (COM). We impose modern municipal boundaries using the historical city code crosswalk available through RIETI (Kondo 2019), and exclude 9 municipalities which merged with another municipality during the last available Census year of 2015. Technopolis sites obtained from Japan Location Center (1999). t-stats computed using heteroskedasticity-robust standard errors.

Table A.3. Summary Statistics for Technopolis Eligible vs. Ineligible Sites

	Eligible	Ineligible	Difference	p-value
Log mfg. employment	8.79	8.37	0.42	0.00
	(1.18)	(1.26)	(0.13)	
Log mfg. establishments	5.44	5.12	0.32	0.01
	(1.25)	(1.19)	(0.12)	
Log mfg. plant capital stock	14.46	13.91	0.55	0.00
	(1.37)	(1.54)	(0.16)	
Log per capita income	6.36	6.42	−0.06	0.02
	(0.16)	(0.24)	(0.02)	
Log Census population	11.27	10.85	0.42	0.00
	(1.21)	(1.07)	(0.11)	
Log population > 65 y.o.	9.02	8.49	0.53	0.00
	(1.15)	(1.00)	(0.11)	
Log median price/m^2 for CRE	10.87	11.17	−0.30	0.02
	(0.71)	(0.90)	(0.13)	
Population density (1000s/km^2)	0.47	1.29	−0.82	0.00
	(0.35)	(2.09)	(0.20)	
Unemployment rate (%)	2.23	2.13	0.10	0.33
	(0.83)	(1.07)	(0.11)	
Ratio of govt. expenditures to revenues	0.98	0.97	0.01	0.03
	(0.01)	(0.03)	(0.00)	
Heavy industry employment share	0.18	0.21	−0.03	0.33
	(0.13)	(0.15)	(0.03)	
Housing expenditure share	0.09	0.10	−0.01	0.59
	(0.02)	(0.03)	(0.01)	
$\%\Delta^{1980-83}$ mfg. employment	9.21	6.21	3.00	0.05
	(21.99)	(13.37)	(1.52)	
$\%\Delta^{1980-83}$ mfg. establishments	5.97	7.39	−1.42	0.27
	(9.21)	(12.82)	(12.46)	
$\%\Delta^{1980-83}$ mfg. capital stock	21.15	21.36	−0.21	0.98
	(50.81)	(79.05)	(7.93)	
$\%\Delta^{1980-83}$ CRE price/m^2	57.74	67.88	−10.14	0.18
	(40.14)	(53.34)	(7.55)	

Notes: The table provides the mean and standard deviation, the unconditional difference in means and standard error, and p-value on the two-sided t-test of the difference between Technopolis-eligible vs. ineligible municipalities. All non-growth rate variables are measured as of the pre-reform period in 1980. Heavy industry employment share is the share of manufacturing (mfg.) employment 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 central business district 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. Government expenditure ratios and unemployment rates also come from the Cabinet Office local statistics. To compute these statistics, we impose modern municipal boundaries using the historical city code crosswalk available through RIETI (Kondo 2019).

A.4 Evidence of Japanese Regional Divergence

As mentioned in the paper's introduction, Japan has experienced an increase in income divergence and directed migration over the last few decades. Panel A of Figure A.3 plots annualized income growth between 1975 and 1995 against initial 1975 log per capita income at the municipality level. The slope of the linear trend-line is negative and marginally statistically significant (t-stat = −1.90), indicating weak income convergence during the earlier boom period. In Panel B, over the next twenty years, and after experiencing the Lost Decade and East Asian Financial Crisis, the slope of the coefficient flips to positive, and is highly statistically significant (t-stat = 8.15), pointing to strong income divergence. On average, every additional 10 log points in initial per capita income is associated with 0.16 additional percentage points in annual growth in total taxable income in the cross-section of modern Japanese cities.

Recent income divergence is driven by depopulation of the countryside and concentration of economic activity in the larger more prosperous metro areas, as shown in Panels C and D of Figure A.3. Following prior research on the U.S. (e.g. Ganong & Shoag 2017), we define directed migration as a positive relationship between regional annual population growth and initial per capita income. During the boom period in which Technopolis was enacted (Panel C), there was already clear directed migration (t-stat = 24.14), which has become stronger in magnitude and in an incremental R-squared sense in the more recent twenty-year period. On average, every additional 10 log points in initial per capita is associated with 0.20 additional percentage points in annual population growth in a city, with an R-squared of 29% and incremental R-squared of 9 p.p. relative to the earlier twenty-year period.

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.

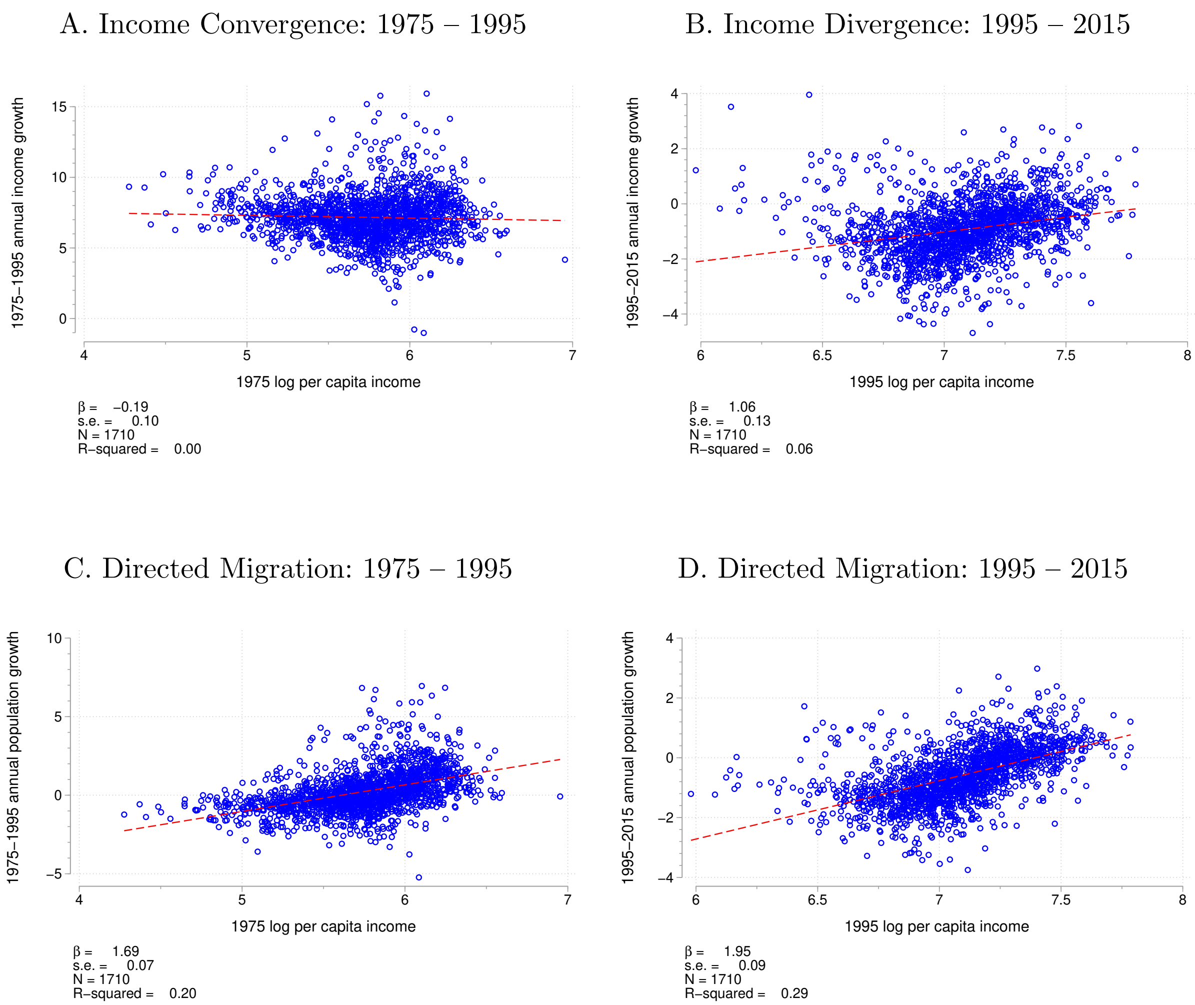
Broad Industry Description	**2-digit Category**	**4-digit Category**
Industrial Machinery & Equipment Leasing	Goods Rental & Leasing	Leasing management General goods leasing Industrial equipment rental Office machinery rental Automobile rental

		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.

FIGURE A.3. Income Inequality and Directed Migration across Japanese Municipalities



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

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 municipal 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).[4]

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.[5] For declining balance, the tax authority calibrates θ_0 such that at $t = x$ only the salvage value remains undepreciated.[6] 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

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

[5]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.

[6]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).[7] 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 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.[8]

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.[9] Assume the lifespan of the PCs is four years, while the lifespan of the new office building is 65 years, as it is in the tax code during our sample period.

Table C.1 summarizes the stream of tax benefit flows for these parameters under the most

[7] 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.

[8] 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.

[9] 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

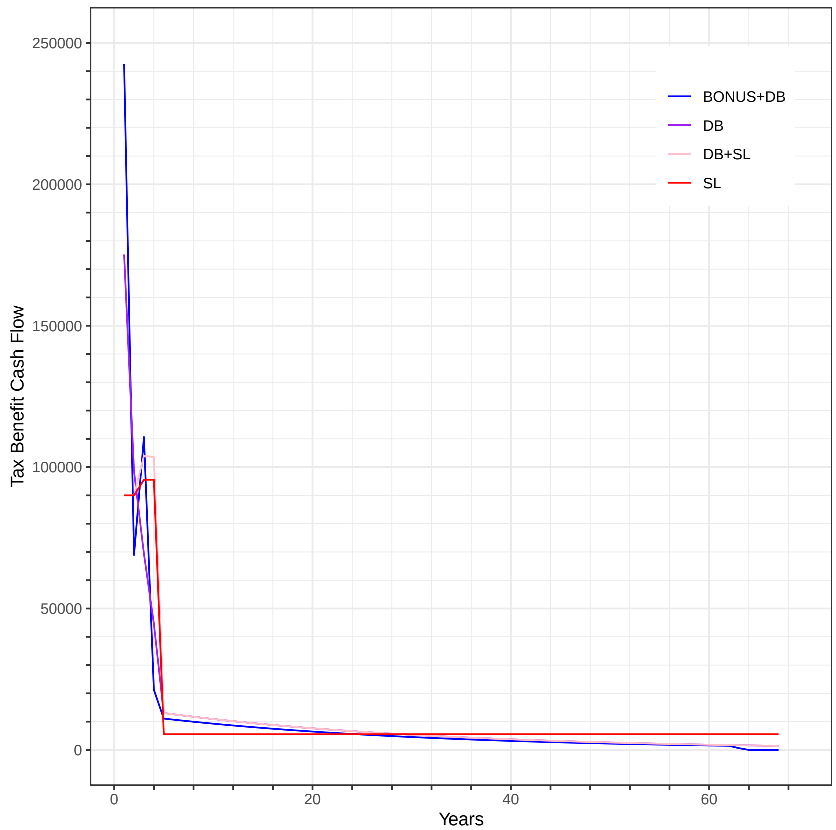
Notes: The table displays year-by-year cash flows from tax benefits of claiming depreciation for the example described in the main text consisting of a \$1 million investment in computers (PCs, lifepspan of 4 years) and a \$1 million investment in constructing a new office building (CRE, lifespan of 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`

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.[10]

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 accounting result underlines our use of the production input share of buildings as a measure of

[10] 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

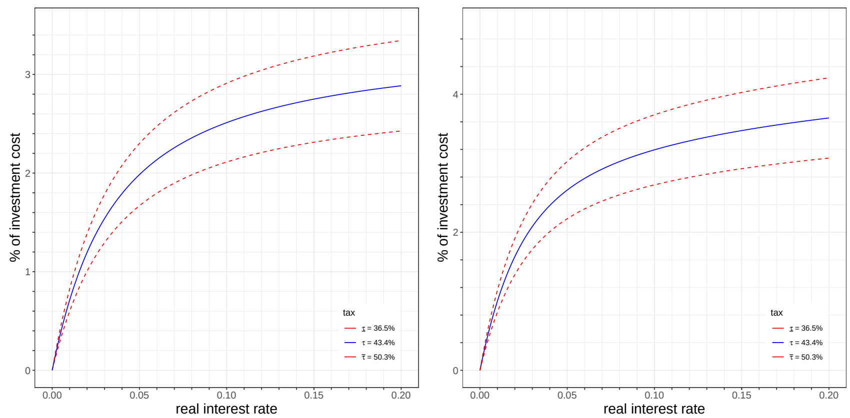


Notes: The figure plots undiscounted tax benefit cash flows over the lifespan of the investment strategy described in the text. We consider four accounting methods: "BONUS + DB" refers to a firm which claims Technopolis bonuses at the maximum possible rate and uses declining balance as it outside option, "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.

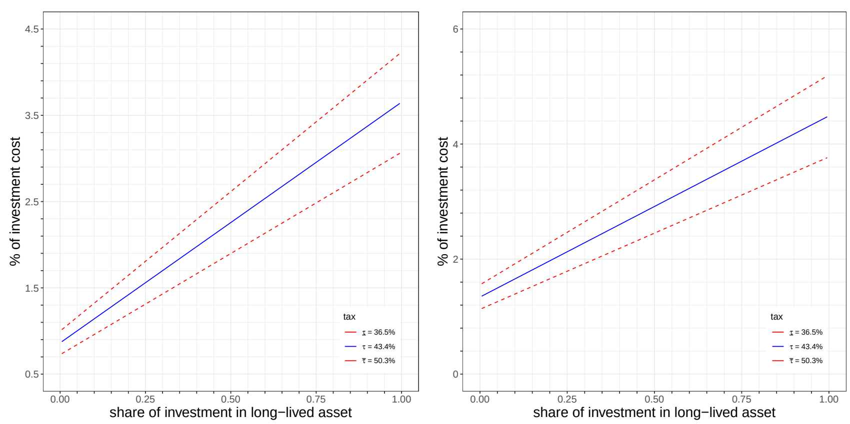
firm treatment intensity in Section 5. At the extreme, a firm investing only in a new building but no computers receives a 4% subsidy (Panel B). Panel C shows that if we applied the 39-year tax lifespan of commercial buildings in the U.S. to the Japanese tax code, the construction subsidy under Technopolis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

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

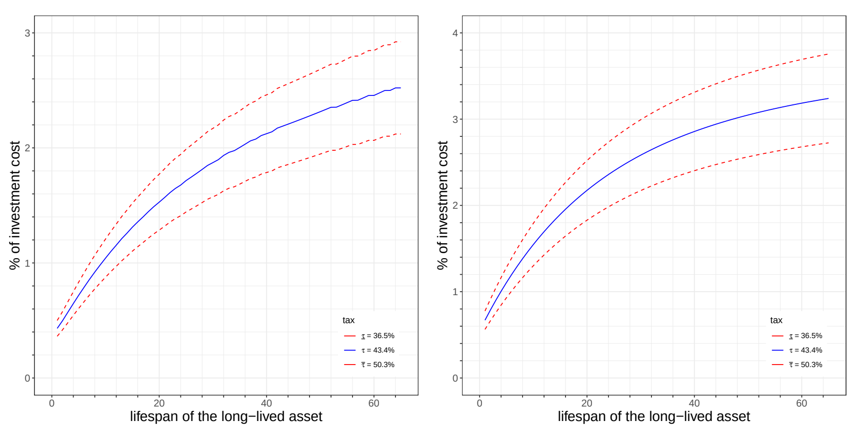
A. Varying the real interest rate



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 Estimation

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.

D.1 Perpetual Inventory Approach

Following Hayashi & Inoue (1991), 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 1980; 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. We feed in the historical corporate income tax rate schedule (plotted in Figure H.2) to pin down u_t. Unfortunately, many firms in our sample do not separately report 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 ($N = 422$).

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 T_j 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, a quadratic in age, whether they use accelerated depreciation methods in the pre-reform period, the Tobin's Q, EBITDA, and the fraction of book PPE comprised of real estate assets. We select this parsimonious set of variables to predict the probability of having non-missing user costs because firms may differ in terms of their bookkeeping methods and the extent to which they enlist a large accounting firm by industry, access to external financing, cash flow, valuation, and reliance on physical capital. 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 (or absolute) 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 estimated factors in $h(X_j)$ from our preferred logit model (column 5) 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. We also check whether more financially sophisticated firms keep more detailed records, although this requires us to drop some firms. Our ability to compute capital input shares loads positively on EBITDA, negatively on the Tobin's Q, and positively on the importance of real estate assets in book PPE. The incremental pseudo-R^2 is the highest moving from column 3 to column 4, where we include the Q ratio and EBITDA. We control for HQ prefecture fixed effects in all specifications. The fact that we are only able to obtain a pseudo-R^2 of 7.84% after adding many key covariates suggests that missing balance sheet values are idiosyncratic and not driven by systematic selection bias.

While our nearest-neighbor approach is potentially vulnerable to how we specify the logit model in (D.5), we find that average implied capital input shares vary minimally across the specifications in Table D.1. The average production share of buildings across firms only ranges from 0.38 in our preferred model in column 5 to 0.40 from the model in column 2. This is reassuring given that ω_{build} is a key parameter determining how the bonus rates offered by Technopolis translate to a subsidy rate (see Table 1).

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, tradables, 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, electronics producers, and service sector firms all have an above-average share of commercial and industrial buildings in their production function. Unsurprisingly, the transportation sector has the highest input share for vehicles.

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 such properties are partially leased from third parties. Most of the profits from leasing companies come from rental income and management of properties. In contrast, manufactured goods-producing firms are more likely to fully own their facilities, and so the building share is highest for those firms. Electronics sector firms often rely on large R&D facilities and thus have a 5 p.p. higher building share than the average.

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.2. Buildings account for an outsize share of production inputs for the majority of firms in our sample, with an average share of 0.38. For all other capital types there is a sizeable mass of firms which have an input share of approximately zero; 36% of DBJ firms have $\omega_{tools} < 0.01$ and 78% of firms have $\omega_{vehicle} < 0.01$. The land share of production is lower than that for 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 commercial building.

D.2 Algorithm Steps

We empirically implement the perpetual inventory approach outlined in the preceding subsection according to the following steps and sets of restrictions:

1. Compute the accounting depreciation rates for each of the six types of fixed assets: buildings, machines, land, structures, tools, and vehicles.

2. Convert assets from book to market value using price indices $Pk_{i,t}$ for each capital input good. We winsorize the resulting capital market values at $\pm 5 \times IQR$ to combat extreme skewness.

3. Convert output $f(K)$ from book to market value by matching firms to a wholesale price index P_t based on their main production sector. We obtain wholesale price indices from the Bank of Japan.

4. Compute effective corporate income tax rates based on observed local tax payments and the top corporate income tax rate according to equation (D.4). In firm-years where the implied rate $\tau_t < 0$ due to capital losses and applied carryforwards, we set the tax rate to be zero. We winsorize τ_t at the 99th percentile to account for extreme outliers due to likely measurement error in how local tax payments are reported (e.g. extra zeros).

5. Set the nominal overall discount factor equal to the inverse of the firm's weighted average cost of capital (WACC), or $\beta_{t,t+1} = 1/(1 + WACC_t)$. In accounting terms, the WACC is:

$$WACC_t = \tag{D.6}$$

6. Calculate the expected present value of tax savings from depreciation $z_{i,t}$ for each asset type. We perform this calculation allowing for bonus depreciation, following the overall depreciation rate calculation in equation (C.2). We compute θ_t^{normal} assuming firms use straight-line depreciation, which leads to more conservative estimates of $z_{i,t}$. Using a declining balance method to compute θ_t^{normal} would require us to impose further assumptions about salvage values which can vary substantially within each goods category. However, the final distributions of ω_i are similar if we assign each firm their modal depreciation method over the panel and for declining balance firms use a constant salvage value stipulated by the tax code under . We discount dollars of depreciation claims using the average short-term prime rate over the 1980s ($r = 0.043$).

7. Use the inputs created in the preceding steps to compute the asset-specific real discount factors according to (D.3).

8. Compute user costs for each asset class according to (D.2).

9. Iterate on the law of motion for each asset class in (D.1) to obtain the real capital series $k_{i,t}$. For each law of motion, we set the 1980 value as the initial condition and then iterate forward. For land, we apply the last-in-first-out (LIFO) inventory correction proposed by Hoshi & Kashyap (1990). For the LIFO correction, we assume that land which is sold was bought at the most recent price paid for land purchases. This means that we amend the

   As noted by Hoshi, Kashyap, & Scharfstein (1991), this correction prevents... Due to the lumpiness of land purchases, this problem remains even though, unlike earlier papers relying on the DBJ data, we use the commercial land indices available at a more granular geographic level provided by LaPoint (2021), which prior researchers did not have.

10. Compute the capital aggregate via:

$$f(K_t) = \sum_{i=1}^{6} (1 - \delta_i) \cdot k_{i,t} \tag{D.7}$$

   where the depreciation rates originate from the procedure in step 1.

11. Using a root solver, we impose the Cobb-Douglas production function in equation (5.2). To estimate $\omega_{i,t}$ for each year, we impose the five tangency conditions that the marginal rate of substitution between two capital inputs equals the ratio of the user costs, along with the constant returns to scale constraint.

12. Finally, we require firms to have a complete series of non-missing $f(K_t)$ over the pre-reform period 1980–1983 and covering the full length of the Technopolis policy period 1984–1995, otherwise we set their input shares to missing. We also set the input shares in any given year to missing if any of the user costs $c_{i,t}$ are computed to be zero, for which there can be multiple possible solutions to (5.2). After completing the preceding steps and imposing this restriction, we match firms with missing values for ω_i to their nearest-neighbor according to the logit model in (D.5), implemented via the specification in column 5 in Table D.1. While this step results in $\omega_{i,t}$, we impose ω_i to be constant by taking the average input share for each firm within each asset class over the pre-reform period 1980-1983, which avoids the possibility that bonus depreciation incentives might have induced firms to change their

production function. Within each firm, the ω_i vary minimally over the sample period.[11]

[11] This results in $N = 422$ firms with non-missing input share series. If we instead only require that firms have non-missing capital aggregates over the pre-reform period, 1980-1983, then this increases our sample of firms with non-missing input shares to $N = 772$, but at the cost of greater measurement error since the latter subsample of firms reports information more sporadically. However, the resulting distribution of shares is similar across both sampling restrictions due to the nearest-neighbor match.

Table D.1. Nearest-Neighbor Matching Logit Model

	(1)	(2)	(3)	(4)	(5)
Assets	0.080	0.079	0.073	0.057	0.179
	(0.190)	(0.193)	(0.193)	(0.212)	(0.214)
Age	0.001	0.001	0.002	0.010	0.011
	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)
Age^2	0.000	0.000	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mfg dummy	0.499***	0.501***	0.478***	0.324**	0.318**
	(0.122)	(0.134)	(0.134)	(0.141)	(0.143)
Services dummy		0.045	0.027	−0.489	−0.677*
		(0.295)	(0.296)	(0.382)	(0.369)
Retail dummy		−0.016	−0.058	0.317	0.078
		(0.224)	(0.225)	(0.244)	(0.254)
DB method dummy			0.669**	0.487	0.326
			(0.289)	(0.318)	(0.325)
Tobin's Q				−0.176	−0.258**
				(0.117)	(0.124)
EBITDA				7.659***	8.807***
				(1.626)	(1.737)
RE/PPE ratio					0.762***
					(0.246)
HQ prefecture FEs	✓	✓	✓	✓	✓
N	1,477	1,477	1,473	1,376	1,376
Pseudo-R^2	0.026	0.026	0.030	0.073	0.078

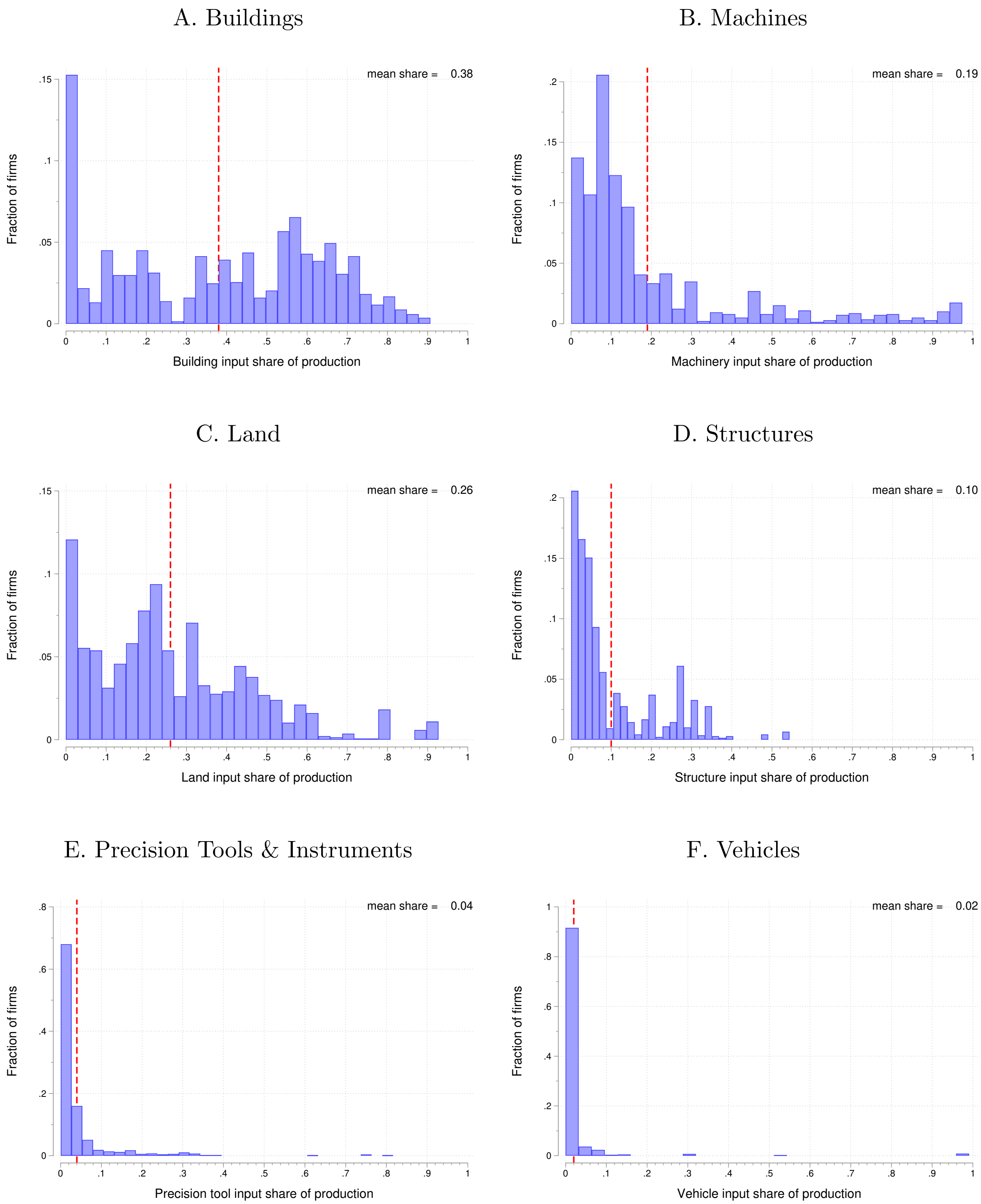
Notes: The table shows the estimated coefficients in $h(\cdot)$ for firm-level characteristics obtained from estimating versions of the logit model in equation (D.5) with the outcome equal to 1 if the firm has all non-missing capital input shares from imposing the perpetual inventory equations. Assets measured as average pre-Technopolis (pre-1984) total assets in 1 billion yen. Age measured from the Tokyo Stock Exchange listing date. We group firms into coarse manufacturing, services, and retail 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 Tobin's Q 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 Tobin's Q are deflated by total assets in the first year before the sample start date and then averaged over the pre-reform period. Heteroskedasticity-robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

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	211	0.357	0.212	0.273	0.110	0.037	0.009
		(0.247)	(0.222)	(0.205)	(0.115)	(0.067)	(0.020)
Heavy manufacturing	492	0.399	0.199	0.249	0.094	0.037	0.020
		(0.262)	(0.229)	(0.197)	(0.105)	(0.069)	(0.102)
Real estate	28	0.346	0.254	0.231	0.116	0.040	0.009
		(0.284)	(0.265)	(0.186)	(0.127)	(0.067)	(0.015)
Construction	106	0.332	0.202	0.240	0.124	0.065	0.036
		(0.277)	(0.236)	(0.191)	(0.134)	(0.149)	(0.138)
Transportation	81	0.301	0.204	0.299	0.103	0.036	0.053
		(0.248)	(0.250)	(0.260)	(0.109)	(0.065)	(0.170)
Electronics	245	0.434	0.156	0.277	0.079	0.042	0.011
		(0.235)	(0.186)	(0.185)	(0.092)	(0.064)	(0.048)
Non-transportation services	79	0.379	0.181	0.262	0.127	0.038	0.009
		(0.272)	(0.194)	(0.272)	(0.131)	(0.092)	(0.015)
Tradables	125	0.326	0.198	0.295	0.107	0.042	0.030
		(0.249)	(0.258)	(0.215)	(0.123)	(0.072)	(0.128)
Agriculture	9	0.500	0.099	0.290	0.059	0.036	0.012
		(0.346)	(0.075)	(0.327)	(0.074)	(0.078)	(0.024)
Overall	1,376	0.380	0.193	0.265	0.100	0.041	0.020
		(0.259)	(0.224)	(0.203)	(0.111)	(0.079)	(0.095)

Notes: The table displays the average input shares (ω_i), with standard deviation 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 nine 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 producers of household appliances, software, and precision instruments. Non-transportation services includes services firms outside shipping and transport. Tradables includes wholesalers and retailers. Agriculture includes fisheries, livestock, and farming.

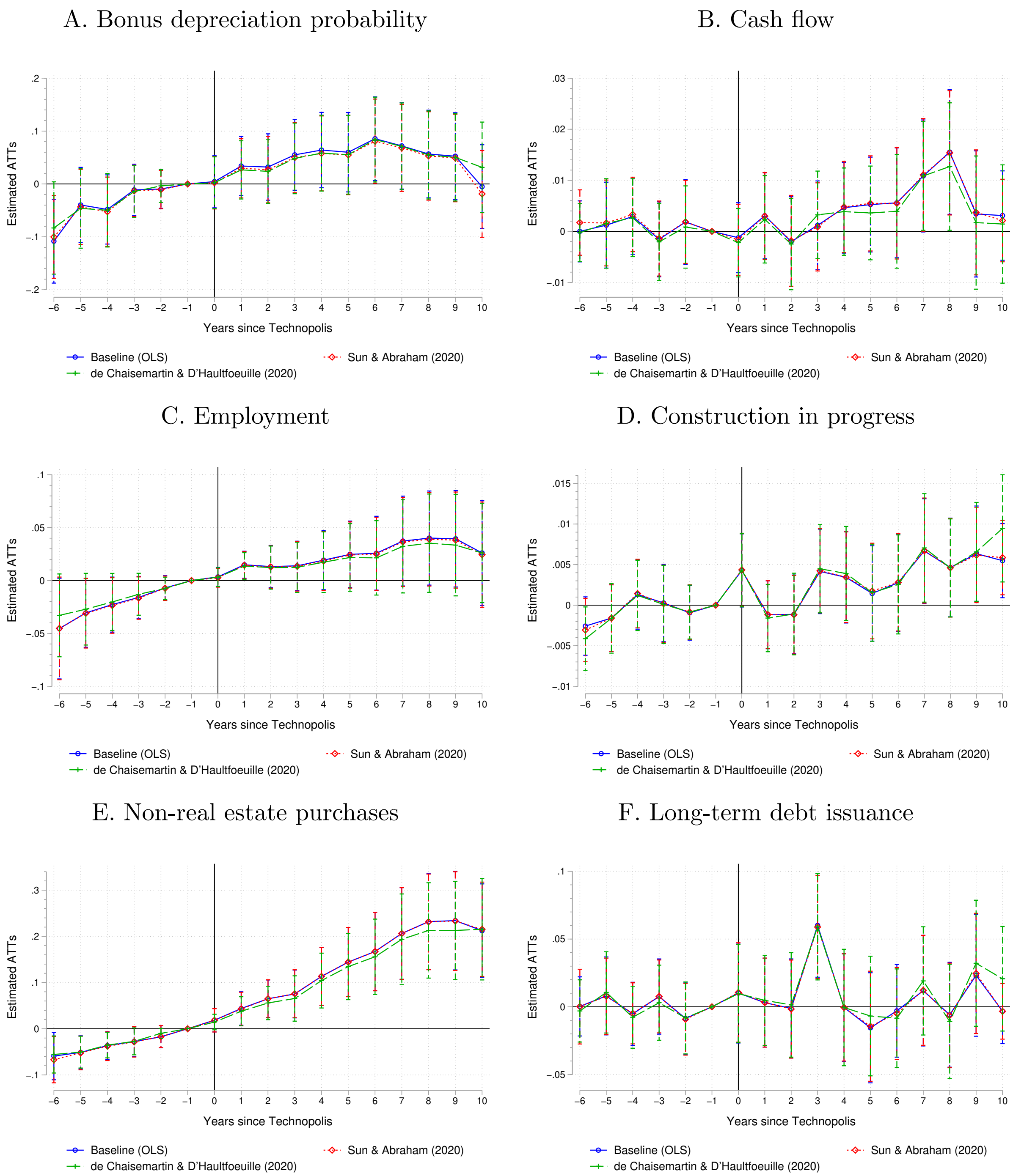
FIGURE D.1. Distribution of Physical Capital Input Shares



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, industrial sector, and firm fundamentals, corresponding to column 5 in Table D.2.

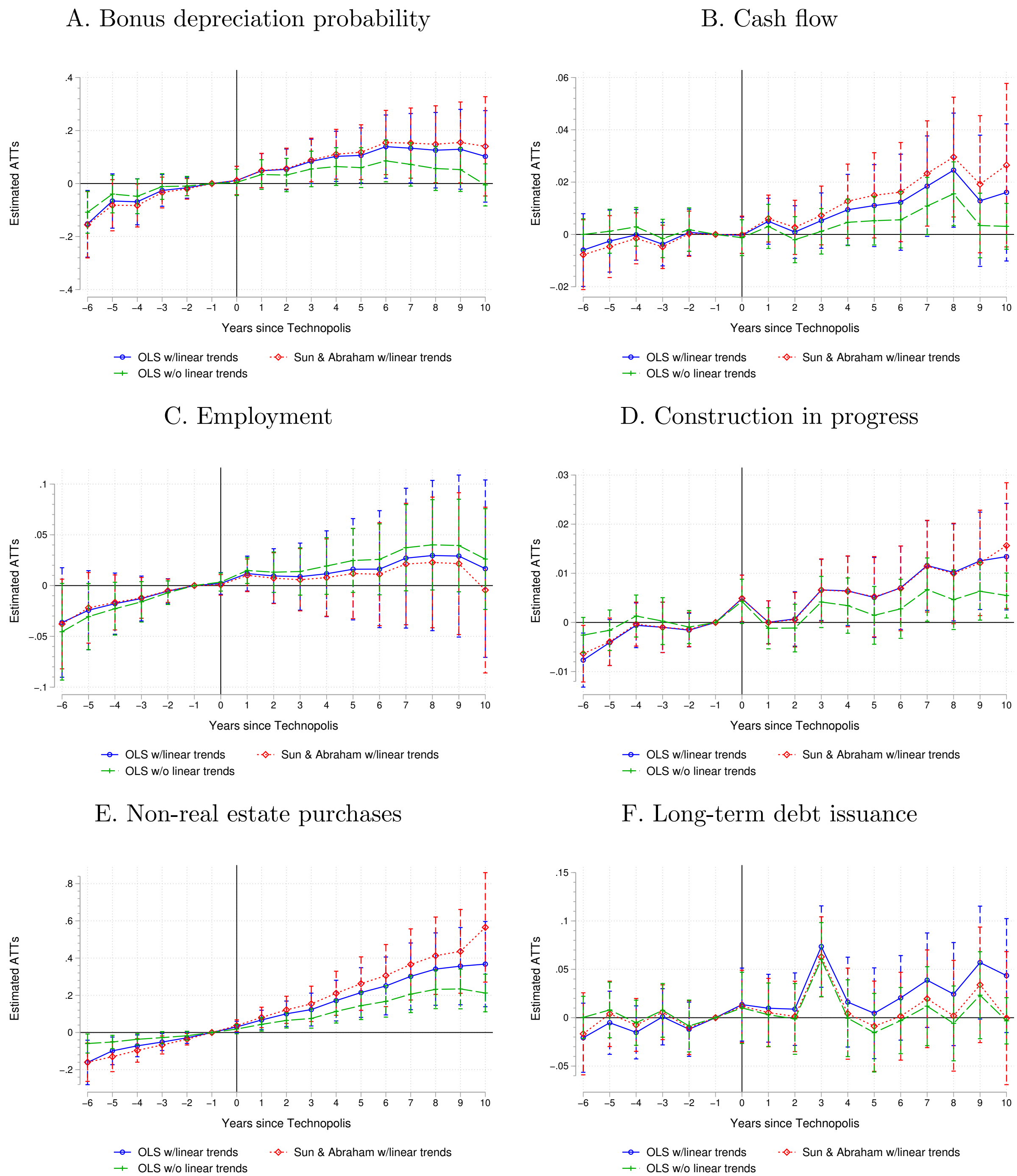
E Main Results Using Other Staggered DD Estimators

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



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



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 × 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 (2023), because these estimators use not-yet treated firms as a control group for which the trends are not identified.

F Trade (Non-)Spillovers of Technopolis

While in Section 5.2.2 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 (2024) 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 $\times$ sector cell. We then interact these prefecture pair $\times$ sector import and export shares with a treatment dummy equal to one if prefecture q contains one of the 26 regional Technopolises.[12] 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.[13]

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

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

$$\text{with} \quad TradeExposure_{j,k,t} = \sum_{p\in\mathcal{J}} \omega^{j}_{p,1980} \cdot TradeExposure^{k}_{p,t} \quad \text{for } \mathcal{J} = \{j_1, j_2, \ldots, j_n\}$$

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

$$\text{and} \quad \text{TradeExposure}^{k}_{p,t} = \underbrace{\sum_{q\neq p} \frac{Imports^{k}_{p,q}}{TotalImports^{k}_{p}} \times Treatment_{q,t}}_{\text{supply}} + \underbrace{\sum_{q\neq p} \frac{Exports^{k}_{p,q}}{TotalExports^{k}_{p}} \times Treatment_{q,t}}_{\text{demand}} \tag{F.2}$$

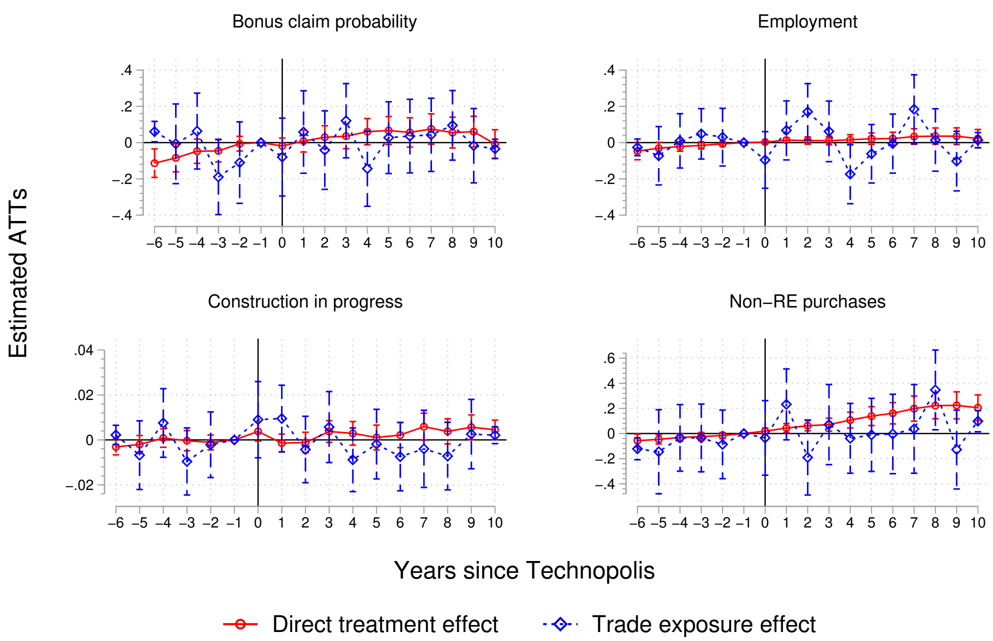
where equation (F.1) describes our augmented event study model, which uses firm-level trade exposure obtained from aggregating the prefecture $\times$ sector exposure measure in (F.2) by taking

[12] 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`.

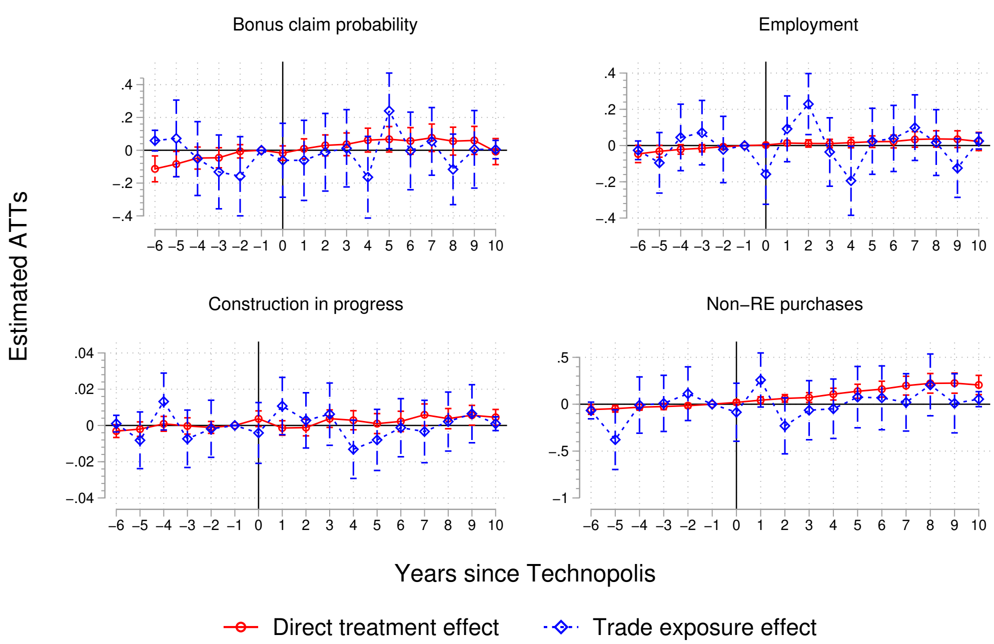
[13] Our results are unchanged if we instead weight by employment across plant locations in 1980, or if we define the treatment dummy in the trade exposure measure at the prefecture $\times$ sector cell.

FIGURE F.1. 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 (F.1) 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.

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 (F.1) where we use only the "supply" or only the "demand" components which link a firm to other firms across the country through trade.

Figure F.1 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 (F.1) and (F.2). 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 3. 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.[14] 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.

G Additional Results & Robustness Checks

G.1 Results for Other Firm-level Outcomes

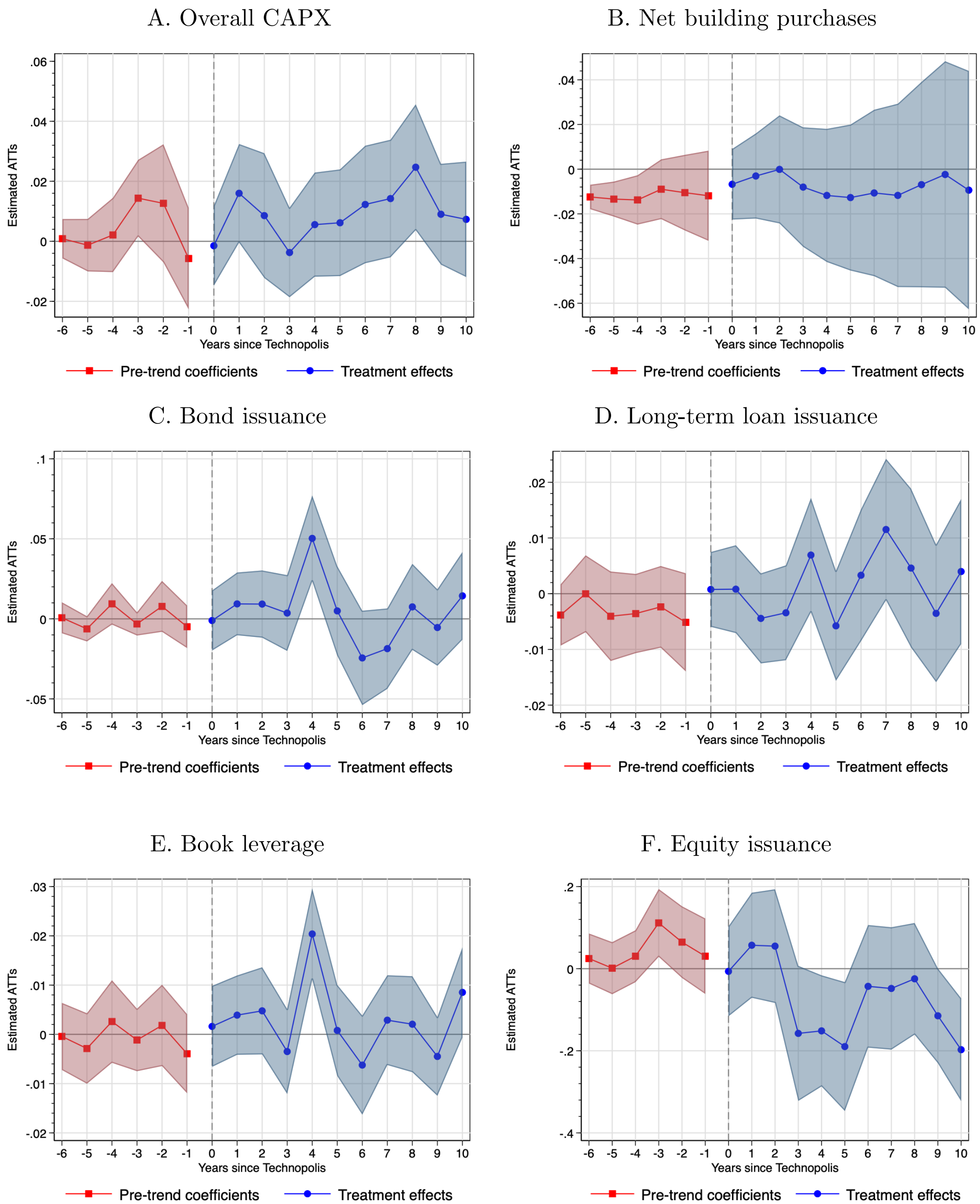
Here we present event study results for other outcomes beyond those we focused on in the main text, including overall CAPX, net building purchases, bond issuance, long-term debt issuance, leverage, and equity issuance. We define overall CAPX as the YOY change in the net book value of PPE plus accounting depreciation. Bond issuance is the YOY change in the book value of total bonds outstanding, including straight, convertible, and subscription bonds. For now, we follow the procedure adopted in the main analysis of deflating monetary values by total firm assets in the year before our sample starts. The exception is book leverage, which we define in a standard fashion as total book debt scaled by total (contemporaneous) assets. We also considered measures of market leverage, such as total book debt scaled by market assets (total book assets + shares outstanding − common equity), but these ratios deliver nearly identical results. Equity issuance is the YOY change in the value of outstanding shares, where the share price is taken as of year-end close.

We refer to building investment as "net" building purchases to emphasize that this CAPX measure includes two competing effects: the increase in the value of buildings on the firm's balance sheet when newly constructed buildings become capitalized, and the decrease in the value of buildings from the purchase of existing buildings. As Figure G.1 indicates, these two effects net out to a zero effect on overall building investment. Bonus depreciation incentives subsidize the construction of new buildings given that older buildings have already substantially depreciated.

Figure G.1 shows that overall CAPX exhibits muted bumps, as acquisitions of non-real estate assets are partially offset by substitution away from land (see Figure 3). While we do not see any clear uptick in issuance of bank loans (Panel D), overall firm leverage spikes around policy year 3 (Panel E), and this is driven by the issuance of bonds (Panel C). Bond issuance following the Technopolis tax break is contemporaneously offset by a reduction in equity issuance (Panel F). These responses are large in magnitude and translate to a 0.25 s.d. decline in equity issuance in year 3 of the policy regime, and a 0.42 s.d. spike in leverage in the same year.

[14] Summing up the import and export exposure measures, as we do in (F.2), also produces very imprecise estimates and no clear monotonicity following policy implementation.

FIGURE G.1. Event Study Results for Other Outcomes



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 (2023). Each regression includes HQ Census region × year fixed effects. With the exception of book leverage, each variable is deflated by the firm's book assets in 1975 before our estimation sample start date. Book leverage is the ratio of total outstanding debt to total assets. Equity issuance is the YOY change in the value of outstanding shares, where the share price is as of year-end close. We winsorize bond issuance, long-term loan issuance, and book leverage at the 2nd/98th percentiles. 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.

G.2 Comparing Cash Flow Measures

Here we document how various measures of cash flow evolve in response to firms' becoming eligible to claim bonus depreciation under the Technopolis policy. In addition to our main first-stage outcome of bonus depreciation claims, we consider three other popular cash flow measures in the accounting and corporate finance literatures: EBITDA, operating cash flow (OCF), and cash flow from net income. The precise accounting definitions of these measures are:

(i) Bonus claims: In the DBJ database bonus claims are included as a line item called, "reserve for special depreciation," separate from accounting depreciation, where the latter includes bonus and non-bonus depreciation costs. Bonus are not available as a separate line item in COMPUSTAT, and our ability to directly observe bonus claims allows us to identify first-stage effects of the Technopolis reform.

(ii) EBITDA: Earnings before interest, taxes, depreciation, or amortization, or operating income + depreciation & amortization. In COMPUSTAT mnemonics this can be computed either simply as EBITDA or OIBD + DP.

(iii) OCF (following Lian & Ma 2021): EBITDA + non-operating income + special items + sale of PPE − income taxes + deferred taxes or refunds + Δ taxes payable + Δ accounts payable − Δ accounts receivable − Δ inventory + Δ unearned revenue − Δ prepaid expenses. In COMPUSTAT mnemonics this can computed as either: OANCF+XINT, or EBITDA + NOPI + SPI + SPPE − TAX − DTAX − ΔATAX + ΔAP − ΔINV + ΔUR − ΔPX + OCFO.

(iv) Cash flow from net income (à la Zwick & Mahon 2017): A common definition of cash flow in the bonus depreciation literature is net income before depreciation, after taxes paid. Or, in COMPUSTAT mnemonics: IBC + DPC.

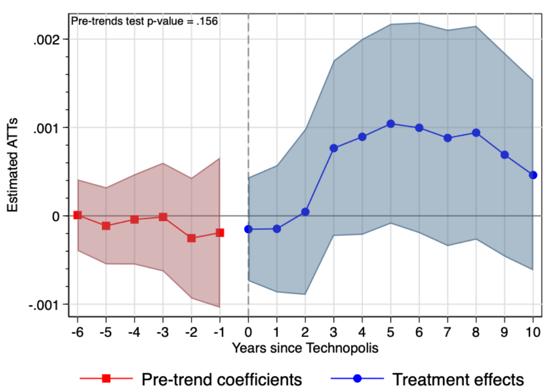
Figure G.2 shows how all four cash flow measures increase after firms are allowed to claim bonuses through Technopolis, with no discernible pre-trends. As in the main text, we use the *BJS* estimator which is robust to treatment effect heterogeneity and include a one-year anticipatory lead. There are some subtle differences between the responses of each measure. Bonus claims (first stage) peak around policy year 5 (a 0.18 s.d. effect) before flat-lining, which corresponds to the final year in which firms can lock in the highest bonus depreciation rate for their physical expenditures. EBITDA does not include receipts from bonus write-offs, but rises steadily, as firms increasing their capital inputs led to increased production capacity. OCF does include receipts from bonus write-offs, and consequently we see a more lumpy response corresponding to the kink points in the bonus depreciation rate schedule in Table 1 and a typical time to build horizon for construction projects of two years. The net income measure of cash flow in panel (iv) does include income from bonuses, since it is net of the tax bill.

G.3 Main Results Using Transformed Outcomes

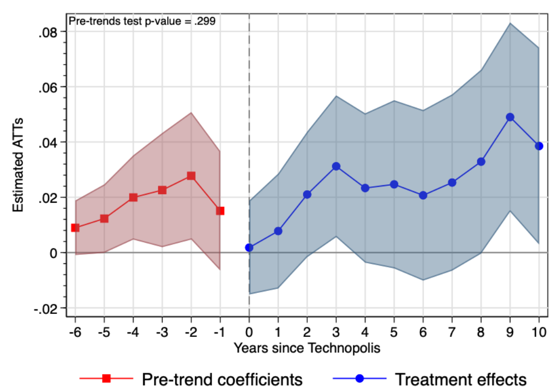
Previously we either scaled outcome variables by total book assets in the year before the start of our sample, or took logs. Specifications in which we used log outcomes (e.g. Panel B of Table 4) can thus be interpreted as intensive margin investment responses. Here we discuss our results when we use the $\log(1+x)$ or inverse hyperbolic sine (IHS) transform $IHS(x)$ to accommodate potential zero values for a variable x. Relative to results presented using log outcomes, these transformed variables allow for extensive margin investment responses to the bonus tax write-offs.

FIGURE G.2. Comparing Dynamic Responses of Cash Flow Measures

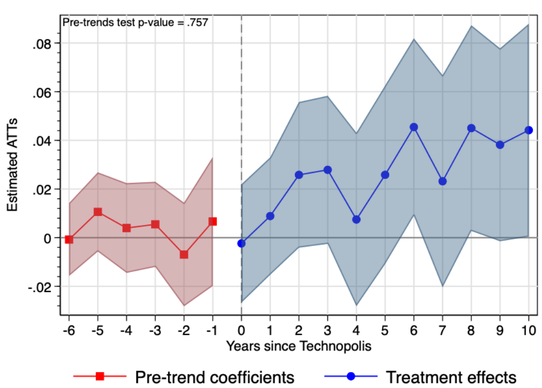
(i) Bonus claims



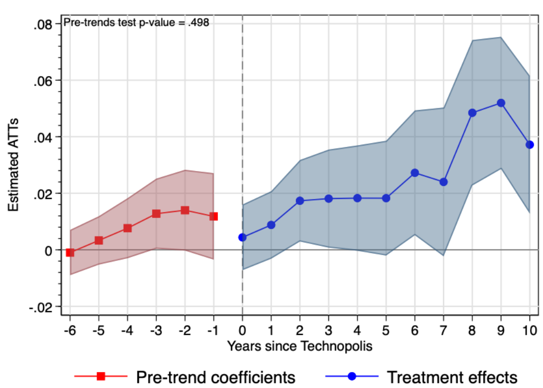
(ii) EBITDA



(iii) Operating cash flow (OCF)



(iv) Cash flow (ZM definition)



Notes: Each panel shows the dynamic response of a cash flow measure estimated via the staggered DD model in equation (4.2) using the imputation estimator method of Borusyak, Jaravel, & Spiess (2023). Each regression includes HQ Census region × year fixed effects. Each cash flow measure is deflated by the firm's book assets in 1975 before our estimation sample start date. 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. Operating cash flow (OCF) in panel (iii) includes income from bonus claims, while EBITDA in panel (ii) does not. The panel (iv) cash flow measure follows Zwick & Mahon (2017) in defining cash flow as net income before depreciation, after taxes paid. See Appendix G.2 text for the precise accounting definition of each cash flow measure.

Our empirical design is a difference-in-differences, meaning that identification of average treatment effects of bonus depreciation on firm outcomes relies on the validity of the parallel trends assumption. Hence, we must also check for pre-trends in transformed variables. To this end, using our preferred estimator [BJS] which is robust to treatment effect heterogeneity, we plot in Figure G.3 the event studies for bonus claims, construction spending, and non-real estate purchases, transformed using either $\log(1+x)$ (left panels) or the IHS transform (right panels). Our results are qualitatively similar to those in Figure 3 for bonus claiming and non-real estate investment, with the former increasing by approximately 20% and the latter increasing by 35% after Technopolis takes effect. In contrast, construction spending evolves differently when we consider the extensive × intensive margin response. There is a 0.10 s.d. spike within the first policy year, before construction spending quickly drops back down to trend. The stark divergence relative to the log and asset-deflated specifications suggests the overall response of construction outlays is dominated by firms who were influenced by the bonus write-offs to break ground on new projects.

G.4 Robustness to Applying Historical Municipal Boundaries

We impose modern municipal boundaries throughout our main analysis to remove the effect of municipal mergers in Japan, which have resulted in a reduction in the number of local jurisdictions from 3,278 in 1980 to 1,741 as of 2015. Using modern boundaries will have the effect of increasing the size of the Technopolis catchment areas, since small towns were absorbed by an untreated regional hub city during the wave of municipal mergers beginning in the 1990s. Historical municipal boundaries offer a stricter definition of treatment; 43 out of 141 contemporaneously treated city codes between 1980 and 2015 become integrated into a generally larger city with a shared border.

Although our results are virtually unchanged for bonus claiming, construction spending, and non-real estate CAPX, Table G.1 and Figure G.4 show that imposing historical boundaries to define firms' treatment status attenuates the measured effect on employment. The point estimates only approach statistical significance at the 10% level for some specifications. This finding is consistent with the "leakage" argument from the plant-level results in Section 5.4. Why? By imposing modern geography, we include some larger city codes which are not part of the official Technopolis boundaries, but are adjacent to treated areas where firms could claim bonuses if they deployed assets to that area. The 2 p.p. reduction in the employment response relative to those in Table 4 and Figure 3 suggests part of the employment response originates from firms claiming bonuses through qualifying investment in an allowed Technopolis area, but staffing treated sites by hiring from a thicker, neighboring labor market.

G.5 Measuring Corporate Distance to Policy Areas

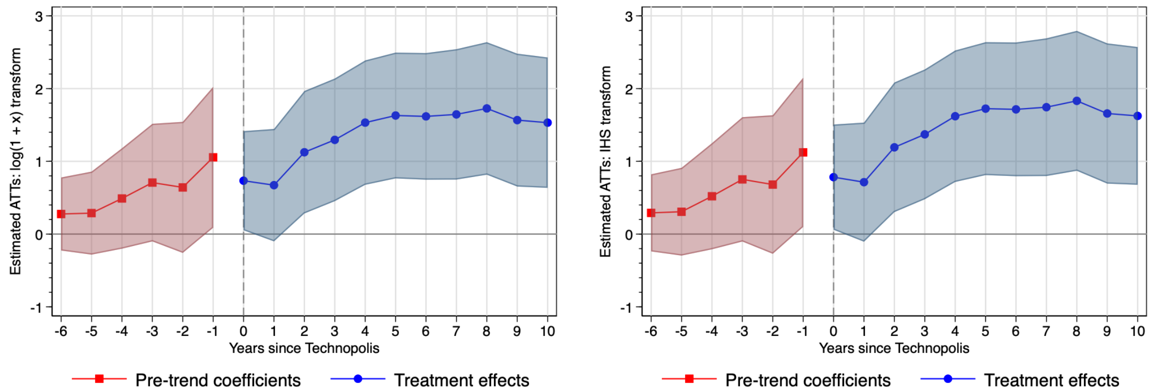
Consider a generalized version of the triple differences specification in (5.5), where the *Distance* variable is a function $f(\cdot)$ mapping individual pairwise distances between the set of plant locations $\mathcal{J} = \{j_1, j_2, \ldots, j_n\}$ to a corporate-level measure of physical distance to the set of Technopolis policy areas $\mathcal{T} = \{1, 2, \ldots, n\}$.

$$\begin{aligned} y_{j,k,t} = \gamma_j + \delta_t + f(dist(\mathcal{J},\mathcal{T})) \times Post_t + Treated_k \times Post_t \\ + f(dist(\mathcal{J},\mathcal{T})) \times Treated_k \times Post_t + \eta' \cdot \mathbf{X_{j,k,t}} + \varepsilon_{j,k,t} \end{aligned} \tag{G.1}$$

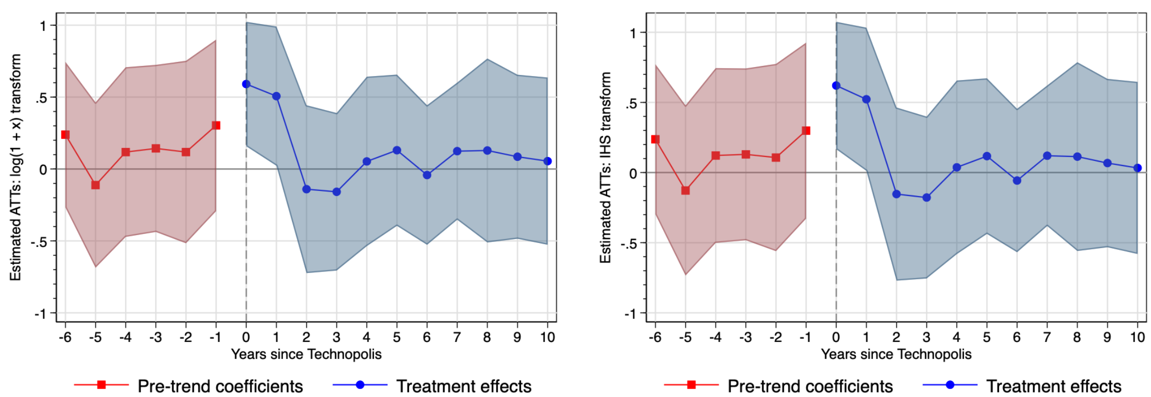
where $dist(\cdot,\cdot)$ is a distance metric which takes as inputs a location in the firm-specific set of locations $\mathcal{J}$ and the set of treated policy locations $\mathcal{T}$ common to all firms. We consider four main

FIGURE G.3. Main Event Study Results Using Transformed Outcomes

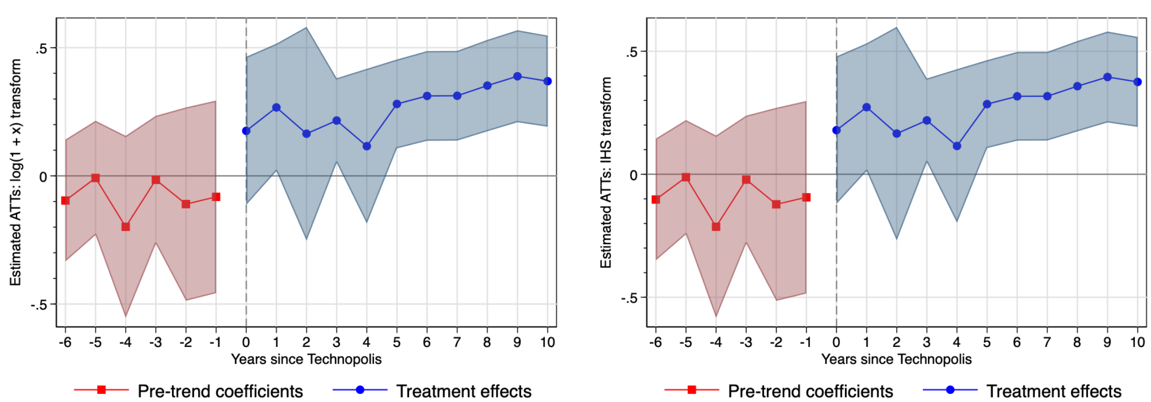
A. Bonus claims



B. Construction



C. Non-real estate asset purchases



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 (2023). The left-hand panels plot estimated treatment effects for variables x transformed using $\log(1+x)$, while the right-hand panels plot treatment effects under the inverse hyperbolic sine function. Each regression includes HQ Census region $\times$ year fixed effects. 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.

Table G.1. Bonus Claiming, Investment, and Employment Responses (Old Geography)

A. First stage: extensive margin bonus depreciation claims

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.091***	0.072**	0.086***	0.093***	0.079**	0.080**
	(0.028)	(0.029)	(0.027)	(0.033)	(0.035)	(0.032)
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

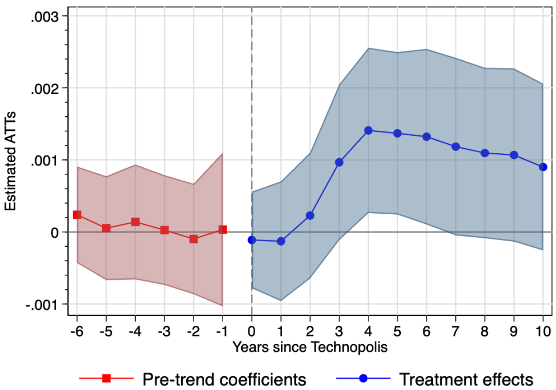
B. Investment and employment responses

	Construction			Non-RE purchases			Employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	0.193**	0.137*	0.225***	0.157***	0.118**	0.161***	0.052	0.019	0.050
	(0.080)	(0.072)	(0.081)	(0.055)	(0.048)	(0.056)	(0.035)	(0.031)	(0.036)
Estimator	OLS	*BJS*	*BJS*	OLS	*BJS*	*BJS*	OLS	*BJS*	*BJS*
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Financial controls		✓			✓			✓	
Controls × year FEs			✓			✓			✓
N	26,996	24,441	27,027	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

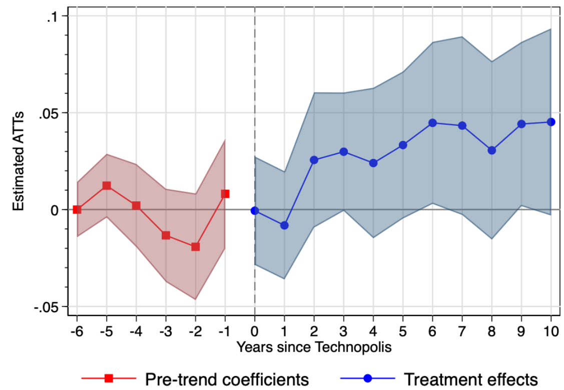
Notes: The table shows results from estimating our staggered DD model in equation (4.1) at the firm level for our main outcomes of interest, pooling all years (1975–2000). The table is analogous to Table 4, except we impose historical municipal boundaries in assigning treatment status. The outcome in 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 purchases is the log gross book value of new PPE excluding buildings, land, and structures, and employment is 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. For the *BJS* estimator, we compute standard errors by taking leave-one-out averages across the cohort treatment effects, which accounts for small cohorts of treated observations and results in more conservative standard errors. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

FIGURE G.4. Dynamic Firm Responses to Technopolis Eligibility (Old Geography)

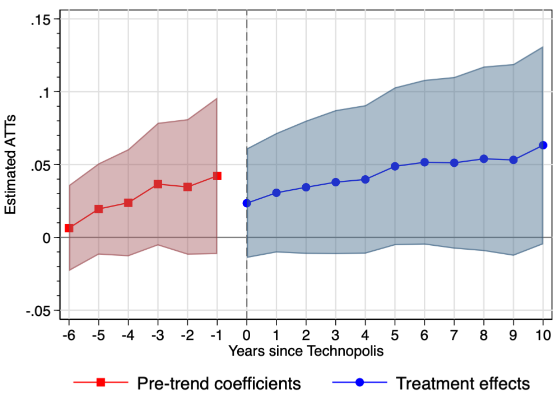
A. Bonus claims



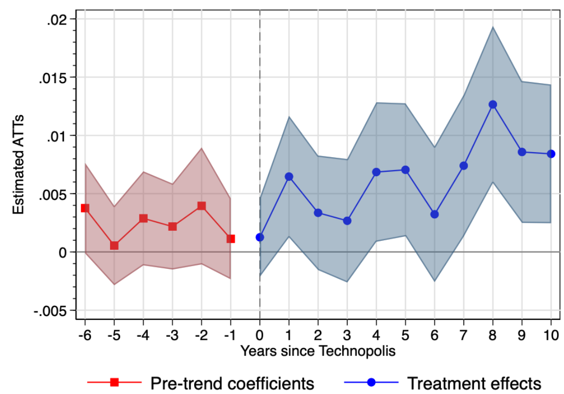
B. Operating cash flow



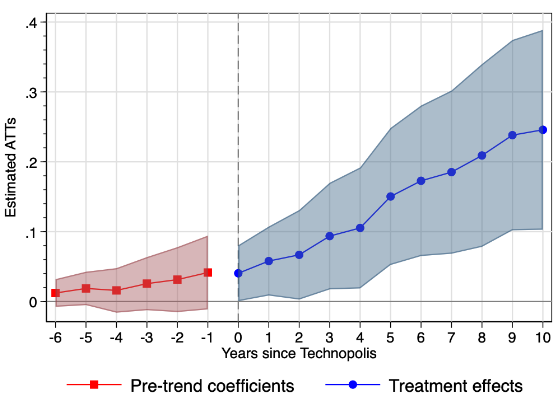
C. Employment



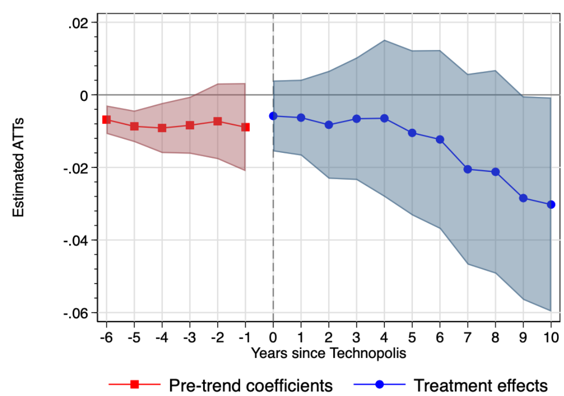
D. Construction in progress



E. Non-real estate purchases



F. Land acquisition



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 (2023). This figure is analogous to Figure 3, except we impose historical municipal boundaries in assigning treatment status. Each regression includes HQ Census region × year fixed effects. With the exception of 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.

weighting schemes implicit in $f(\cdot)$:

$$f(dist(\mathcal{J},\mathcal{T})) = \min_{p\in\mathcal{J}} \left\{ \min_{\tau\in\mathcal{T}} dist(p,\tau) \right\} \quad \text{(minimum distance)} \tag{G.2}$$

$$f(dist(\mathcal{J},\mathcal{T})) = \frac{1}{|\mathcal{J}|} \sum_{p\in\mathcal{J}} \left\{ \min_{\tau\in\mathcal{T}} dist(p,\tau) \right\} \quad \text{(average distance)} \tag{G.3}$$

$$f(dist(\mathcal{J},\mathcal{T})) = \sum_{p\in\mathcal{J}} \omega^{j}_{p,1980} \cdot \left\{ \min_{\tau\in\mathcal{T}} dist(j,\tau) \right\} \quad \text{(share-weighted average distance)} \tag{G.4}$$

In each case, for each plant location p within the firm's network, we compute the minimum distance between p and all possible Technopolis city codes in the set $\mathcal{T}$. We then require a way to aggregate across all plants p, which is how the distance measures differ. Equation (G.2) computes a minimum distance between the firm and all policy regions in that it represents the shortest possible distance between firm operations and an area where CAPX is eligible for bonus claims. Equation (G.3) takes an equal-weighted average distance between plants and each plant's nearest Technopolis, and (G.4) instead takes a share-weighted average. We compute share-weighted average distances in (G.4) using either initial capital shares or employment shares across locations $p \in \mathcal{J}$. For instance, we compute capital shares as:

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

using 1980 as the base year since we have detailed coverage in the corporate filings for that year which allow us to observe itemized book PPE for each firm j and location p.

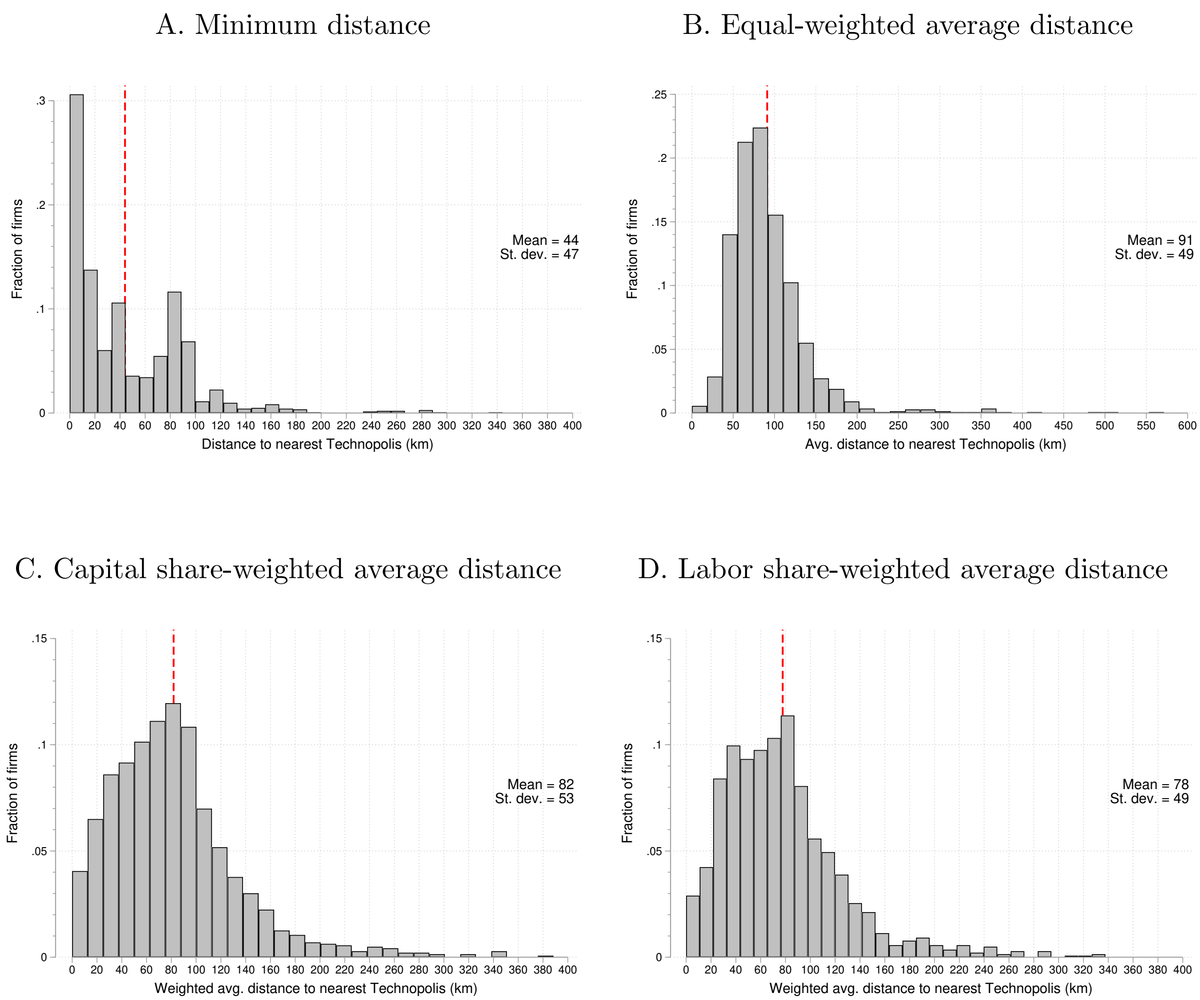
To empirically implement (G.1), we use the `georoute` package of Weber & Péclat (2022), combined with the Here API, to create a matrix of all truck driving distances between the center of each pair of modern city code locations in Japan. We retrieved latitude/longitude of each city code center based on its city hall location.[15] The `georoute` package adopts modern routes and thus ignores the non-viability of certain routes during our historical policy period. We then match each firm to a vector of distances between its pre-existing set of plant locations and the policy areas to compute $f(\cdot)$. Our results are also nearly identical if we drop from the sets $\mathcal{J}$ any locations on the island of Shikoku, which was more geographically isolated from the rest of Japan prior to the completion of the Great Seto Bridge in 1988. Our results are qualitatively similar, albeit less precisely estimated, if we instead use Haversine distance. However, given how mountainous Japan is, geodesic distance is a weak proxy for the costs of transporting inputs and workers between firm locations.[16]

Table G.2 shows how policy take-up declines with measures of firm distance according to the model in (G.1) and the metrics defined by (G.2)–(G.4). The coefficient of interest is the triple interaction term $Distance \times Treated \times Post$ which captures how the propensity of firms in eligible industries to claim bonus depreciation changes with notions of physical distance to the policy

[15] The PDFs containing the city hall locations can be found here: `https://www.gsi.go.jp/KOKUJYOHO/center.htm`.

[16] Another alternative would be to use distance between firm locations and the closest point among the borders of treated jurisdictions. We do not take this approach because detailed address information is only available for a subset of plant locations during the earlier portion of our sample, and such an approach assumes that firm activity in the policy areas – to the extent that it exists – would be conducted on the periphery instead of in the CBD.

FIGURE G.5. Distribution of Firm-level Distance to Policy Areas



Notes: Panel A shows the distribution of firm-level policy area distances computed via (G.2), Panel B via (G.3), and Panels C and D via (G.4) for different definitions of $\omega^j_{p,1980}$. Panel C uses initial net book PPE shares at each plant location, while Panel D uses employment shares. Vertical red lines indicate the average distance in kilometers.

Table G.2. Policy Take-up Response to Distance Measures

	Min. distance		Avg. distance		RE-wgt. distance		Emp-wgt. distance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance × *Treated* × *Post*	−0.045	−0.056*	−0.099**	−0.117***	−0.084**	−0.075**	−0.100**	−0.104***
	(0.035)	(0.034)	(0.040)	(0.040)	(0.033)	(0.034)	(0.037)	(0.036)
Distance × *Post*	−0.062**	−0.007	0.000	0.022	0.010	0.022	0.045**	0.069***
	(0.020)	(0.020)	(0.019)	(0.021)	(0.013)	(0.016)	(0.020)	(0.021)
Treated × *Post*	0.118***	0.132***	0.176***	0.209***	0.162***	0.169***	0.167***	0.184***
	(0.027)	(0.027)	(0.042)	(0.042)	(0.035)	(0.035)	(0.036)	(0.035)
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls × year FEs		✓		✓		✓		✓
N	34,520	34,520	34,773	34,773	34,695	34,695	34,326	34,326
# Firms	1,355	1,355	1,365	1,365	1,362	1,362	1,347	1,347
Adj. R^2	0.515	0.534	0.514	0.535	0.514	0.535	0.513	0.536

Notes: Each column in the table presents results from estimating equation (G.1) via pooled OLS, with a dummy for bonus depreciation claiming $\mathbb{1}\{bonus > 0\}$ as the outcome variable. We rescaled estimates with $Distance_j$ so that the effect is the change in probability of claiming given a 100 km increase in distance. The columns differ in the function $f(\cdot)$ used to map distances between plant locations to a corporate-level measure of distance to the Technopolis policy areas. See text and equations (G.1)–(G.4) for complete definitions. 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. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

areas. Consistent with intra-firm transport costs, a firm with plants at an average distance of 100 km from the nearest Technopolis area is 10% less likely to make bonus claims during the policy regime. The results are much weaker using the minimum distance measure in (G.2). We conjecture this is because – as the distributions of each firm-level distance measure in Figure G.5 show – most large firms already have a plant operating either within a Technopolis site or within 10 km of one. Indeed, 43% of firms have a plant within a qualifying area as of 1980.

H Fiscal Cost & Cost-Per-Job Calculations

In this appendix, we assess the cost-effectiveness of Technopolis by converting the difference-in-differences estimates of Section 5 to cost-per-job measures.

H.1 Baseline Cost-Per-Job Estimates

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:

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

where we compute the fiscal cost from 1984 ($t = 1$) through 1995 ($t = T$), 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.[17] Corporate income tax rates vary between 43.3% and 37.5% during the policy period, and for a given tax year the rate is the same for all corporations with above $80,000 in taxable earnings.[18] The gap between D_t^{bonus} and D_t^{normal} represents the difference in benefits per dollar of investment accruing 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:

$$D_t^{normal} = \xi \cdot D_t^{DB} + (1 - \xi) \cdot D_t^{SL} \tag{H.2}$$

where ξ is the share of firms who choose declining balance.[19] 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.

The last component of the accounting identity is the take-up rate, or the share of firms which are both classified within 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 fiscal cost of 1.5% per dollar of qualifying capital investment from (H.1).

A final step is needed to produce the fiscal cost in dollars. We compute aggregate qualifying CAPX among our firms over the policy period by summing up the firm-level changes in the gross book value of physical capital excluding land between 1984 and 1995. We remove land from CAPX in computing the D_t benefit flows and aggregate qualifying CAPX because land does not depreciate. This results in $1.56 trillion in corporate CAPX (136.6 trillion JPY), but not all of this investment satisfied the industry and location eligibility criteria for bonuses. We thus scale down total CAPX by computing the share of eligible investment among manufacturing firms for which we have investment itemized by plant location:

$$\frac{\sum_{t=0}^{T} \sum_i \Delta PPE_{i,t} \times Treatment_{i,k,t}}{\sum_{t=0}^{T} \sum_i \Delta PPE_{i,t}} \tag{H.3}$$

where $Treatment_{i,k,t}$ is equal to one if plant i is located in a Technopolis area and attached to

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

[18] We obtained the historical corporate income tax rate series from a 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 8 million JPY threshold. None of the publicly listed firms qualifies for the lower rate in any year of our sample.

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

a parent firm in industry k that is one of the treated 4-digit JSICs. $\Delta PPE_{i,t}$ refers to the YOY change in the net book value of non-land physical assets, plus accounting depreciation, or investment in non-land assets. The investment eligibility rate implied by (H.3) is 6.6%, resulting in \$102.75 billion in eligible corporate CAPX conducted under Technopolis. The fiscal cost in dollars amounts to \$102.75 billion $\times$ 1.5% = \$1.54 billion.[20]

It is far more straightforward to compute a measure of jobs generated by Technopolis. Our preferred DD estimate of the employment response from Figure 3 is 5%. Scaling up average total employment in the pre-period among listed firms in eligible industries by 5% implies 68,342 corporate jobs created, leading to a cost per job of \$1.54 billion/68,342 $\approx$ \$22,222. If we instead use our pooled OLS estimate (Table 4) of a 7% bump in employment, then 96,650 jobs were created, and the cost per job falls to \$15,714.

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 (H.1) is an *ex post* fiscal cost, whereas estimates in the literature assume a change in the average benefit rate implied by a simulated cost amortization schedule or another study, and then apply that percentage to aggregate CAPX eligible for the tax break to produce an overall dollar value cost. Using time-variation in $D_t^{bonus} - D_t^{normal}$ is more appropriate in our setting, given the event study evidence in Figure 3 that bonus claiming activity under the policy was concentrated soon after enactment, implying higher fiscal costs in a PDV sense than if we assumed a constant gap $D^{bonus} - D^{normal}$. On the other hand, our access to balance sheets is predicated on a firm being publicly listed, so our measure only recovers the fiscal cost per large corporate job.[21]

Our estimates lie at the low end of those reported in the place-based policy literature, as pictured in Figure H.1. Bartik (2020) and Criscuolo et al. (2019) survey cost-per-job estimates (in real 2010 USD) from comparable policies featuring business subsidies and find a wide range, from the \$18,295 estimate for Empowerment Zones provided by Busso, Gregory, & Kline (2013), to the \$68,409 estimate for Italian Law 488 of Cerqua & Pellegrini (2014). The local heterogeneity in bonus depreciation exposure analyzed in Garrett et al. (2020) is perhaps the most similar natural experiment to Technopolis, and those authors report a \$20,000 cost per job using county $\times$ industry-level data, the fiscal cost expression in (H.1), and assuming a 2.13% subsidy rate for national bonus depreciation tabulated in Zwick & Mahon (2017) from corporate tax returns. We emphasize that our results apply to *corporate* jobs created, and as Section 5.4 indicates, the leakage of jobs to larger cities may result in lower fixed hiring costs for specialized labor in thicker labor markets compared to the relatively thin skilled labor markets of Technopolis sites.

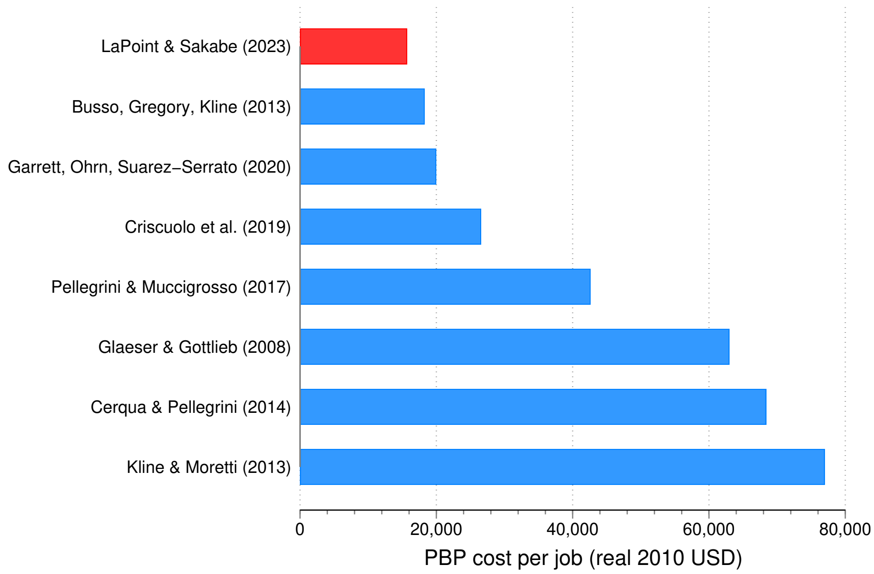
H.2 Alternative Cost-Per-Job Counterfactuals

Key to producing the above fiscal cost calculations is assuming a proxy for counterfactual depreciation claims firms would have made in the absence of the place-based incentives of

[20] Our cost-per-job numbers likely overestimate the true fiscal cost, because the factor we apply from (H.3) to pare down total CAPX to eligible CAPX is calculated across manufacturing plants, which we know were already more concentrated in areas designated as a Technopolis cluster. However, our fiscal cost estimates fall between 2%-3% per dollar of qualifying capital investment, which agrees with the cash flow simulations we perform in Appendix C to estimate subsidy rates for different firm investment profiles.

[21] 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 (H.2) for D_t^{normal} we can obtain from cash flow simulations like those in Appendix C.

FIGURE H.1. Comparison of Place-Based Policy Cost-Per-Job Estimates



Notes: Estimates from studies reporting cost-per-job estimates for place-based policies with investment subsidies. Following Criscuolo et al. (2019), to convert annual cash flows from nominal JPY to real USD, we apply the historical exchange rates from the University of British Columbia Pacific Exchange Rate Service (available at `https://fx.sauder.ubc.ca/`) and then convert to real USD using the all items U.S. CPI-U.

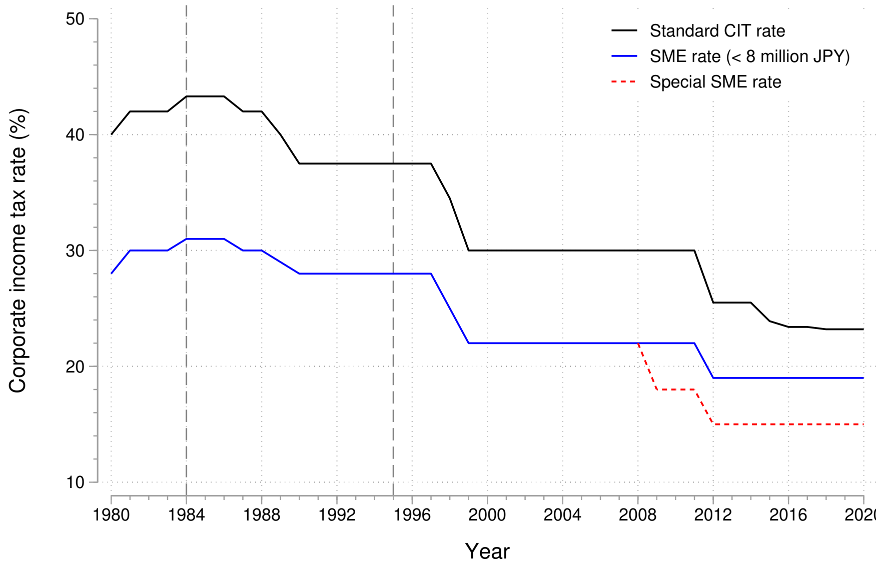
Technopolis. The accounting identity in equation (H.1) says that the fiscal cost is the PDV of tax revenues lost as a result of offering Technopolis bonus depreciation. Corporate income tax rates τ_t are flat across large firms but vary over time according to the standard rate series (black line) pictured in Figure H.2. As a baseline, we take D^{bonus} to be total depreciation claims divided by total CAPX less land investment among bonus-claiming firms, and take D^{normal} to be the same ratio except computed over the set of firm-years who do not claim bonuses.

Our baseline exercise implicitly assumes that firms only claim bonuses through Technopolis, and not through other provisions in the tax code. While this assumption largely holds true, bonus depreciation was allowed for certain special asset classes (e.g. airplanes) even when Technopolis was not applicable. Unfortunately, we do not observe a separate line item for bonus depreciation specifically claimed under Technopolis or its companion policy of Intelligent Location. For shorthand, define D^{gap}, as the dollar value of additional claims due to Technopolis bonus and D^{total} as the dollar value of all depreciation claims. We consider several alternative counterfactual definitions that may be used to back out the fiscal cost, summarized as follows:

- **Version A (baseline):** Compare D_t^{total}/I_t of bonus claiming to non-claiming firms. This method includes some policy ineligible firms who still can claim bonuses under the normal tax regime.

- **Version B (first differences):** Compute $\overline{D_t^{gap}/I_t} - D_{pre}^{gap}/I_{pre}$ accruing only to the eligible firms. This is a first differences calculation comparing the average fraction of bonus claims among Technopolis-eligible firms in each policy year to the average fraction of bonus claims D_{pre}^{gap}/I_{pre} among Technopolis-eligible firms in the pre-reform period (1975 – 1983).

FIGURE H.2. Corporate Income Tax Rate Time Series



Notes: Historical corporate income tax (CIT) rates plotted from the Ministry of Finance series available here: https://www.mof.go.jp/tax_policy/summary/corporation/c01.htm. The standard CIT rate (black line) applies to firms with nominal earnings greater than 8 million JPY within the tax year, while the SME rate (blue line) applies to firms earning below this threshold. The special SME rate (dashed red line) is a transitional rate that applies in a newly formed company's first tax year if earnings are below the threshold. The standard CIT rate applies to all firms in our main analysis sample for which we have corporate balance sheet information.

- **Version C (difference-in-differences):** Calculate the difference in means represented by

$$\left(\overline{D_t^{gap}/I_t} - D_{pre}^{gap}/I_{pre}| \text{ eligible}\right) - \left(\overline{D_t^{gap}/I_t} - D_{pre}^{gap}/I_{pre}| \text{ ineligible}\right)$$

  This is a difference-in-differences calculation where we take the Version B estimate and subtract off the change in the average fraction of bonus claims between the pre and post-reform period for the Technopolis-ineligible firms.

- **Version D (regression DD):** The method we adopt in Section 6 uses a residualized version of the Version C difference-in-differences estimate in which we run the following regression:

$$D_{j,k,t}^{gap}/I_{j,k,t} = \gamma_j + \sum_{t=1975}^{1995} \left(\beta_t \cdot Treated_{j,k,t} \times Post_t + \textbf{Controls} \times \delta_t\right) + \varepsilon_{j,k,t} \tag{H.4}$$

  Here we define $Treated_{j,k,t}$ as equal to unity if firm j is in an industry k eligible for bonus claims under Technopolis. $Post_t$ is an indicator for the post-1984 period. For this exercise, we shut down time variation in the policy rollout across locations to account for bonus claiming on the extensive margin of firm entry into an eligible catchment area. The vector **Controls** includes fixed effects for 1980 HQ Census region, 1980 balance sheet size quintile, and age quintile. By interacting these time-invariant controls with a complete set of fixed effects, $\widehat{\beta_t}$ represent the estimated average percentage cash flow benefit of Technopolis bonus claims, comparing two firms in the same part of the size and age distribution and with an HQ in the

Table H.1. Sensitivity Analysis of Fiscal Cost-per-job Estimates

	A: Baseline	B: 1st diff in means	C: DD in means	D: Residualized DD
$r = 5\%$; $\widehat{\beta}^{emp} = 5\%$	\$55,430	\$52,672	\$37,011	\$26,659
	[3.69%]	[3.50%]	[2.46%]	[1.77%]
$r = 7\%$; $\widehat{\beta}^{emp} = 5\%$	\$43,556	\$45,439	\$30,525	\$22,222
	[2.90%]	[3.02%]	[2.03%]	[1.48%]
$r = 5\%$; $\widehat{\beta}^{emp} = 7\%$	\$39,135	\$33,931	\$21,584	\$16,781
	[3.69%]	[3.50%]	[2.46%]	[1.77%]
$r = 7\%$; $\widehat{\beta}^{emp} = 7\%$	\$30,799	\$32,130	\$18,818	\$15,714
	[2.90%]	[3.02%]	[2.03%]	[1.48%]

Notes: The table shows cost-per-job estimates (real 2010 USD) for different parameter estimates using the accounting identity in (H.1) for lost cash flows from offering bonus depreciation. Brackets indicate the fiscal cost as a percentage of a dollar of capital investment that qualifies for bonuses. In each method we compute the denominator of D_t/I_t using the YOY change in the net book value of PPE excluding land, plus accounting depreciation. To calculate aggregate CAPX eligible for Technopolis bonus claims, we scale down total corporate CAPX using the eligibility ratio computed via (6.3). See Appendix G.6 text for complete descriptions of the counterfactual definitions underlying each method.

same region. We then feed the $\widehat{\beta}_t$ for $1984 \leq t \leq 1995$ into equation (H.1) as our measure of the benefit per dollar of eligible CAPX derived from Technopolis, $D_t^{bonus} - D_t^{normal}$.

Table H.1 summarizes the cost-per-job amounts and fiscal cost percentages (in brackets) obtained under each of the four counterfactual definitions described above. For methods B,C, and D, we winsorize $D_{j,k,t}^{gap}$ at the 2nd/98th percentiles, given the extreme skewness of the distribution of bonus claims and a median D^{gap} of zero. For $r = 7\%$ and our more conservative DD estimate of $\widehat{\beta}^{emp} = 5\%$ for the employment bump generated by Technopolis, the estimates from the first three versions range from \$30,525 to \$43,556 per corporate job, or 2%-3% in terms of the net subsidy rate. These fiscal cost percentages match the cash flow simulation exercises we perform in Appendix C, wherein a typical firm with a long-lived asset share around 50% recoups 2% to 3% of investment costs through Technopolis bonus allowances. Version D produces the lowest cost estimates because it is based on a more local policy treatment, comparing two firms in the same HQ region $\times$ size $\times$ age cell, where one receives bonus allowances and the other does not. Version D produces fiscal cost estimates which are closer in spirit to the average treatment effects on the treated (ATT) represented by $\widehat{\beta}^{emp}$.

I 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

Table I.1. Firm-level Results with Separate Policy Treatments

	Bonus claim		Construction		Non-RE purchases		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 (I.1) 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 purchases is the log gross book value of new PPE excluding buildings, land, and structures, and employment is 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. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

by expanding the catchment areas and extending bonus incentives to firms engaged in high-tech services (e.g. software) and precision instruments manufacturing. Due to the spatial overlap of Technopolis and Intelligent Location (cf. Figure 1), and the fact that Intelligent Location industries were in many cases upstream 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 3 may reflect such local general equilibrium effects, we augment our baseline staggered DD specification to account for firms' eligibility under the Intelligent Location criteria:

$$y_{j,k,t} = \gamma_j + \delta_t + \beta_1 \cdot Treatment^T_{j,k,t} + \beta_2 \cdot Treatment^{IL}_{j,k,t} + \eta' \cdot \mathbf{X_{j,k,t}} + \varepsilon_{j,k,t} \tag{I.1}$$

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, 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 I.1 provides results for our main outcomes of interest from estimating the multiple treatment regression in equation (I.1). We plot the dynamic effects of the $Treatment^T$ and $Treatment^{IL}$

dummies in Figure I.1. First, we observe that the estimates for β_1 are quantitatively similar to those reported in Panel B of Table 4. 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. 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 acquisitions (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 employment and output in catchment areas to service proximal upstream firms who expanded under Technopolis.

Directly interpreting $\widehat{\beta_2}$ in Table I.1 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 (2023) analyze regressions like our equation (I.1) 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 (2023) 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:

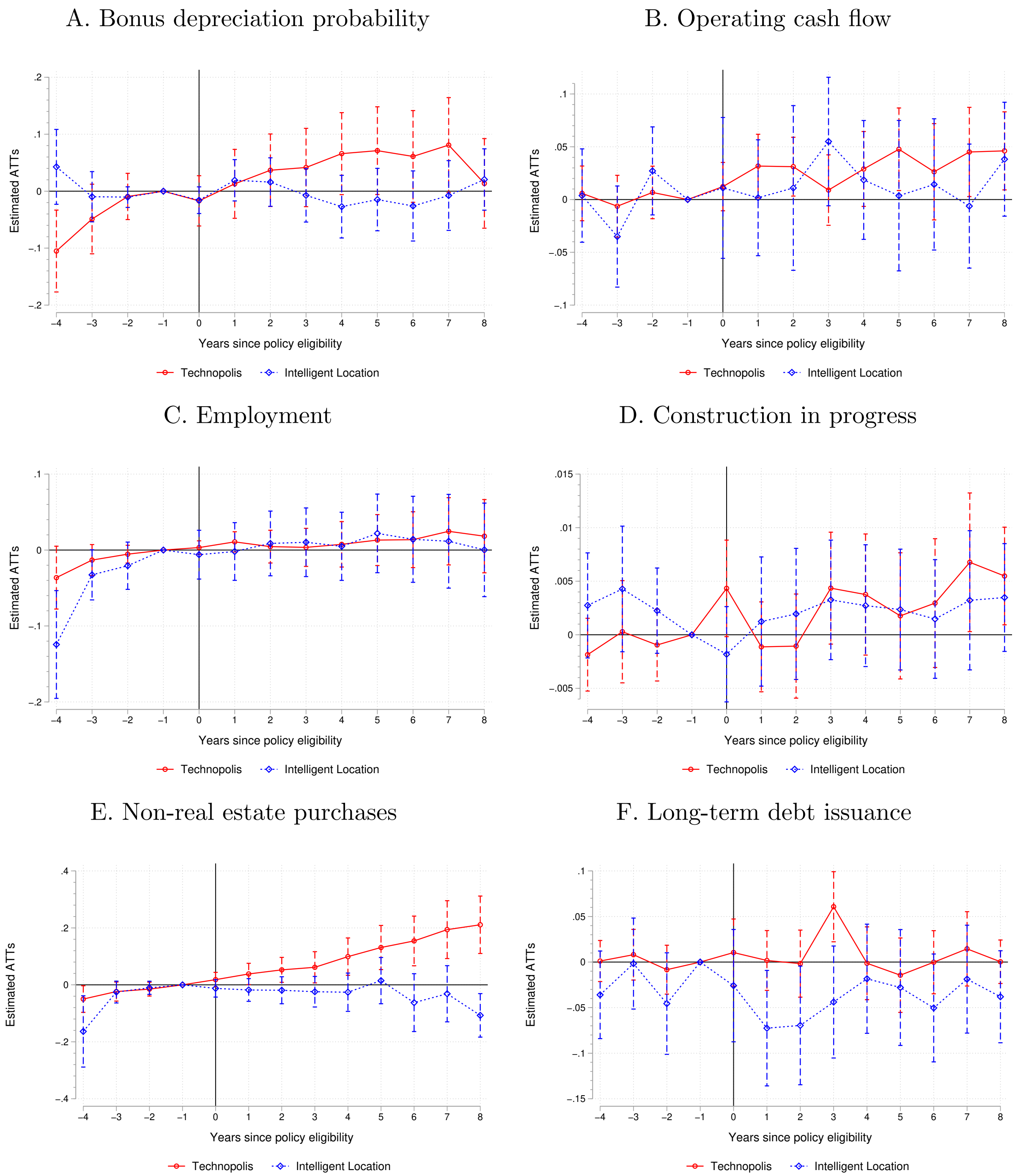
$$y_{j,k,t} = \gamma_j + \delta_t + \sum_{t=1, t\neq t_0}^{T} \beta_{2,t} \cdot Treatment^{IL}_{j,k,t} + F^{T}_{j,t} + \varepsilon_{j,k,t} \tag{I.2}$$

which mirrors our previous event study equation from Section 4, but with two key differences. First, we only estimate (I.2) 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.[22]

Figure I.2 plots the dynamic treatment effects of the Intelligent Location policy obtained from estimating the model in (I.2) 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 I.1. 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

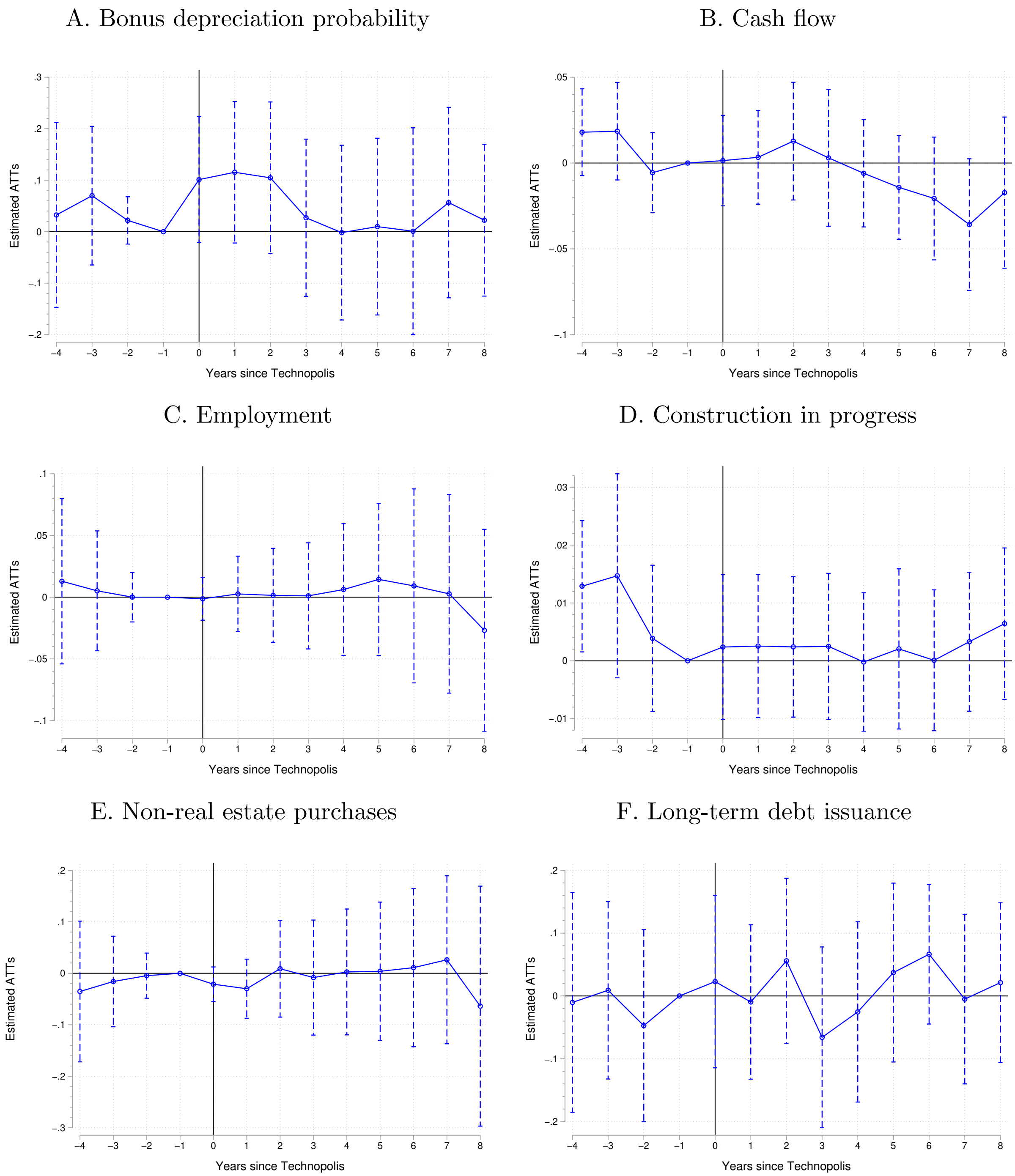
[22] Goldsmith-Pinkham, Hull, & Kolesár (2022) also consider multiple treatment regressions. They derive efficient estimators for separating treatment effects under the assumption of conditional independence (i.e. under a set of controls), while the de Chaisemartin & D'Haultfœuille (2023) approach relies 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 $\beta_{2,t} \rightarrow \beta_{2,t+1}$ 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 I.1. 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 (I.1) 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.

FIGURE I.2. 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 (I.2) using the estimator proposed by de Chaisemartin & D'Haultfœuille (2023). 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.

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 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.

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