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Place-Based Policies and the Geography of Corporate Investment*

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Abstract

We estimate the dynamic effects of place-based tax incentives on local investment, job creation, and firm relocation decisions using a series of policy experiments in Japan as our laboratory. The Japanese government rolled out the Technopolis program between 1984 and 1989, offering firms bonus depreciation rates as high as 30% towards tangible capital investment in economically peripheral regions. A follow-up policy enacted in 1989 expanded the set of eligible areas and increased bonus depreciation for firms in certain non-tradable industries. Using detailed multi-plant firm balance sheet data and several staggered difference-in-differences (DD) approaches, we find both policies generated employment and investment in building construction and non-real estate assets, with little evidence of spillovers to ineligible firms in treated areas. The effects are driven by more financially constrained firms and firms which rely on relatively long-lived assets such as buildings in their operations. Our results point to the importance of providing large and immediate rather than deferred financial incentives for inducing firms to make irreversible investments in struggling regions.

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

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

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1 Introduction

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

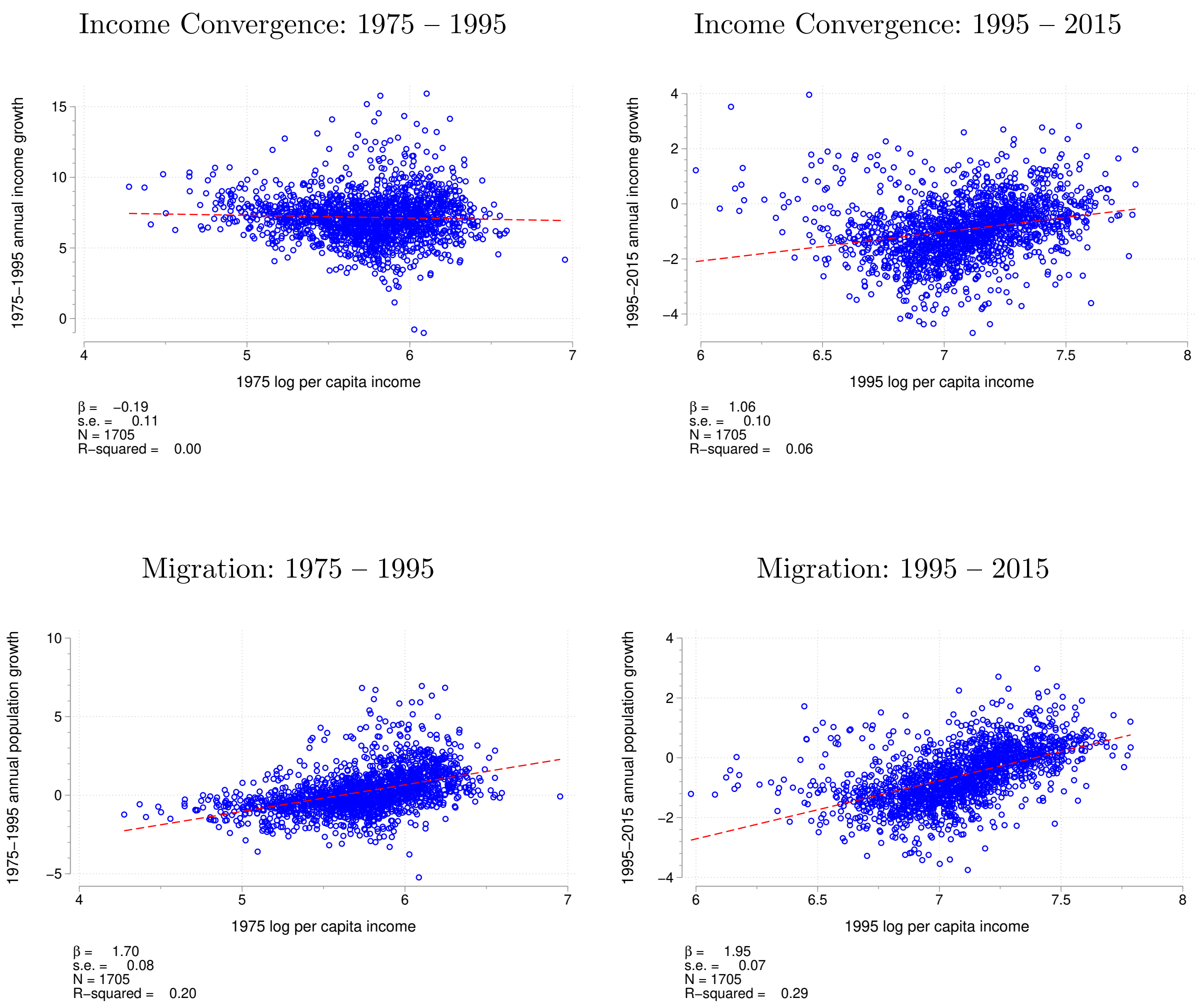
To answer these questions, we leverage detailed balance sheet data matched to the Japanese manufacturing Census to examine the footprint of place-based policies (PBPs), like the Foxconn deal, on the geographic distribution of physical capital investment and job creation. Determining the efficacy of PBPs is of central importance given the widely documented growth in spatial inequality coinciding with the decline of traditional manufacturing since the 1970s. For instance, in the last three decades the U.S. has witnessed a stark decline in per capita income convergence (Ganong & Shoag 2017) and prime-age male employment rates (Austin, Glaeser, & Summers 2018), but a convergence in poverty rates across locations (Gaubert et al. 2021). Figure 1 shows that Japan has experienced an increase in directed migration and income *divergence* over the last few decades, as population aging has exacerbated the depopulation of the countryside and economic activity becomes increasingly concentrated around Tokyo.

Japan presents a useful laboratory to evaluate the short-run and long-run outcomes of PBPs due to its early experimentation with several initiatives in the 1980s and 1990s to promote industry clusters outside the Greater Tokyo metro area. The Japanese government rolled out the Technopolis program between 1984 and 1989, which offered manufacturing firms bonus depreciation rates as high as 30% towards physical capital expenditures, including purchases of buildings used for business operations. A follow-up policy enacted between 1989 and 1994, dubbed Intelligent Location, expanded the set of eligible areas and offered bonus depreciation to firms in certain non-tradable industries, with the maximum rate rising to 36% for firms headquartered in Central Tokyo who opted to open a new plant in a catchment area.

Using a series of staggered difference-in-differences specifications, we find both policies were successful at generating investment in treated areas. The historical nature of the Japanese policy experiments and long time coverage of our data allow us to examine the long-run impact of local business tax incentives on regional economic development. In particular, we rule out "toe dipping," or firms making small reversible investments to capture tax benefits and then exiting shortly thereafter. For listed firms, capital and employment shares within a firm's internal network are

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

FIGURE 1. Income Divergence across Japanese Municipalities



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

stable three decades after the bonus depreciation incentives expired. Moreover, this investment response was in the form of construction projects on existing sites within the firm's network of plants; we find granting firms Technopolis eligibility generated a 0.24 standard deviation increase in outlays for construction, and a 0.27 standard deviation increase in non-real estate assets.

Place-based policies are a catch-all term referring to transfers made conditional on economic activity in a location, but such policies can take many forms. The vast majority of research on PBPs has covered state and local tax subsidies and restricted attention to short-run effects due to data limitations (Bartik 2020). An exception is Kline & Moretti (2014), who study the Tennessee Valley Authority (TVA) over the century since its founding and conclude the TVA boosted national manufacturing productivity but employment gains were reversed when subsidies ended. De Simone et al. (2019) compile a comprehensive database of firm-specific U.S. local tax subsidies and contend the most successful subsidies are granted in jurisdictions where the initiatives receive little press coverage. Devereux, Griffith, & Simpson (2007) document that relocation grants in the U.K. were only effective at attracting plants when the new location already had plants of the same industry, suggesting the industry targeting of PBPs like Technopolis and Intelligent Location is crucial to the success of these policies. Criscuolo et al. (2019) study the same setting in the U.K. and find large effects on manufacturing employment for small firms, but larger firms "game the system" by accepting subsidies without increasing local activity.[2]

Much of the recent empirical literature on PBPs analyzes the Opportunity Zone (OZ) program introduced by the 2017 U.S. Tax Cuts and Jobs Act (TCJA) to foster local job growth. The program allows state governors to designate low-income Census tracts as OZs, subject to Treasury Department approval. Investors can defer capital gains taxes on investment in OZs for at least five years, or eliminate their tax liability entirely if they hold the assets for at least 10 years. Freedman, Khanna, & Neumark (2021) conclude these tax incentives had no statistically significant impact on resident employment, earnings, or poverty rates. Similarly, Chen, Glaeser, & Wessel (2019) document minimal capitalization into single family home prices, suggesting that homebuyers do not expect neighborhood change resulting from the OZ program in the near term. Arefeva et al. (2020) instead find designated OZ Census tracts experienced increased employment growth of 2-4 p.p. between 2017 and 2019.

In recent work, Kennedy & Wheeler (2021) note using investors' tax returns that the gains from OZs are highly unequal, with relatively well-off and gentrifying Census tracts receiving the bulk of investment under the OZ program. This raises the question: what are the distributional consequences of place-based policies? We approach this question from two angles. First, we look at spillovers to a control group of firms located in eligible Technopolis sites who are ineligible to claim bonus depreciation due to their industry classification. We find no evidence of positive spillovers, but some evidence of cannibalization with respect to non-real estate investment. Second, we match

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

our sample of listed firms to their establishments and show that firms' hiring and intensive margin investment were concentrated in Technopolis *ineligible* areas. Thus, while we do not find evidence of toe-dipping, we uncover suggestive evidence that firms used the cash flow benefits of Technopolis to redirect resources towards areas not targeted by policymakers.

Two main features distinguish our policy setting from related local business incentive schemes in the U.S. First, our results point to the importance of providing *immediate* rather than deferred financial incentives for inducing firms to make irreversible investments in struggling 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 deferral incentives of OZs. Second, the Technopolis and Intelligent Location policies we study are set at the national level, which limits the role of local political economy concerns (Slattery & Zidar 2020), or tax competition between jurisdictions (Mast 2020), in determining selection of treated regions and industries. In our policy setting, eligible locations are chosen on the basis of their manufacturing capacity and proximity to research universities, with incentives funded through national rather than local tax revenues.

Research on the economic impacts of PBPs has overwhelmingly examined wages and employment outcomes. In contrast, in this paper we focus on how tax incentives can shift the spatial distribution of physical asset expenditures by mitigating frictions in capital markets. Such frictions might include financial constraints, as emphasized in a large corporate finance literature (e.g. Giroud & Mueller 2015, 2019), investment adjustment costs or "time to build" (Cooper & Haltiwanger 2006), and the costs of transporting tangible assets between locations (Ma, Murfin, & Pratt 2020). In a closely related paper, Zwick & Mahon (2017) demonstrate that firms with longer-lived assets like heavy industrial equipment exhibit larger investment responses to the 2001, 2003, and 2008 U.S. bonus depreciation reforms, which is consistent with models featuring fixed adjustment costs or financing constraints.[3]

When we rank firms based on measures of external financing constraints popular in the empirical corporate finance literature (e.g. Hadlock & Pierce 2010), we find that constrained firms completely drive the take-up of bonus claims, investment, and hiring. We recover firms' capital input shares using the methods of Hayashi & Inoue (1991) to rank firms based on their reliance on long-lived vs. short-lived assets. Assuming a constant returns to scale production function, buildings account for 47% of the capital input share for the average listed firm in our sample. This is particularly important because in the absence of bonus depreciation, commercial use buildings have a depreciation life as long as 65 years, implying a tax deduction *per annum* of only 1.54%

[3]There is a voluminous empirical literature analyzing the investment response to corporate tax breaks. This literature has largely ignored the spatial dimension of investment. Notable examples include Goolsbee (1998) and Chirinko, Fazzari, & Meyer (1999) on investment tax credits; Desai & Goolsbee (2004) and Yagan (2015) on the 2003 U.S. dividend tax cut; House & Shapiro (2008) and Edgerton (2010) on bonus depreciation. Boissel & Matray (2020) find that a major hike in the French dividend tax rate induced firms to cut dividend payments and use the increase in liquidity to increase investment. The latter result is at odds with the two main camps in public finance: the "Old View," which says payout tax increases stifle investment, and the "New View" of payout taxes, which says payout taxes have no effect on investment (Moon 2020).

of the acquisition cost under straight-line depreciation.[4] The outsize share of properties in firm production, combined with the maximum bonus depreciation claim of 15% for buildings under the two PBPs, renders relocation and outright ownership of new plants (or expansions of existing plants) in the treated regions substantially more attractive. Bonus depreciation is thus an especially potent force towards fostering irreversible investment.

Finally, our paper lends empirical support to mechanisms introduced in a growing macro-trade literature modeling the location decision of firms on the extensive margin (i.e. where to set up shop) and the intensive margin – that is, how many resources to allocate to a particular location. Gaubert (2018) builds a model with agglomeration in which firms sort across cities on the extensive margin and argues PBPs like Technopolis and Intelligent Location which subsidize smaller cities have negative aggregate effects. In Fajgelbaum et al. (2018) firms sort into states which offer lower corporate income tax rates, and tax competition between states diminishes aggregate welfare. Like Jia (2008) and Holmes (2005, 2011), Oberfield et al. (2020) allow for sorting on both the extensive and intensive margin; their framework adds cannibalization and span of control and transport costs, but does not allow the physical size of plants to vary across locations. Importantly, none of these models directly includes capital in firm production, even though Dougal, Parsons, & Titman (2015) document agglomeration forces operating through capital rather than labor inputs.[5] As emphasized in LaPoint (2020), incorporating physical capital and financing constraints into a spatial sorting model can generate huge output responses to policy changes. We view our work as a critical first step towards putting capital back into models of spatial firms to assess the aggregate effects of place-based policies.

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

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

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

2 Policy Background

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

For both policies, we obtain the schedule of bonus depreciation rates from Ministry of International Trade and Industry (1995), which describes eligible asset classes and facilities at the 4-digit Japan Standard Industry Classification (JSIC) level. We provide in Appendix A a full list of eligible JSIC industries for each policy. We now summarize the tax incentives and eligibility criteria for each program in greater detail.[6]

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 (Okubo & Tomiura 2012).

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

Rather than featuring direct subsidies to either firms or local governments, Technopolis locations offered businesses a bonus depreciation schedule, where the bonus percentage declined beginning

[6] We provide the complete tables for eligibility criteria by industry, area, and implementation date in the appendix.

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

TABLE 1. Technopolis Bonus Depreciation Incentives

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

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

five years after the initial eligibility date specific to that location. Table 1 lists the full schedule as a percentage 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 to 65 years for 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 30% – the average corporate income tax rate among firms in our data in 1990 – this implies an immediate cash flow benefit from bonus claims of \$135,000. 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 \$79,620 in immediate cash flow from tax savings. While the Technopolis bonus depreciation claims expired 12 years after implementation (e.g. by 2001 for the Technopolis designated in 1989), businesses could still claim the usual straight-line depreciation rate that applied to each asset class regardless of investment location.

The final dimension of Technopolis eligibility is the industry classification of the corporate tax unit.[8] We create a crosswalk to convert the historical Japan Standard Industry Classification codes (JSICs) valid under Technopolis to the modern classification system and report the full list of eligible

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

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. Source: Ministry of International Trade and Industry (1995).

industries in Appendix A. Of the 555 manufacturing industry codes, 66 JSICs (13%) are treated by Technopolis, including firms producing textiles, chemicals, pottery and ceramics, non-ferrous metals, machinery, precision tools, electronics, computers, and vehicles.

2.2 The Intelligent Location Policy

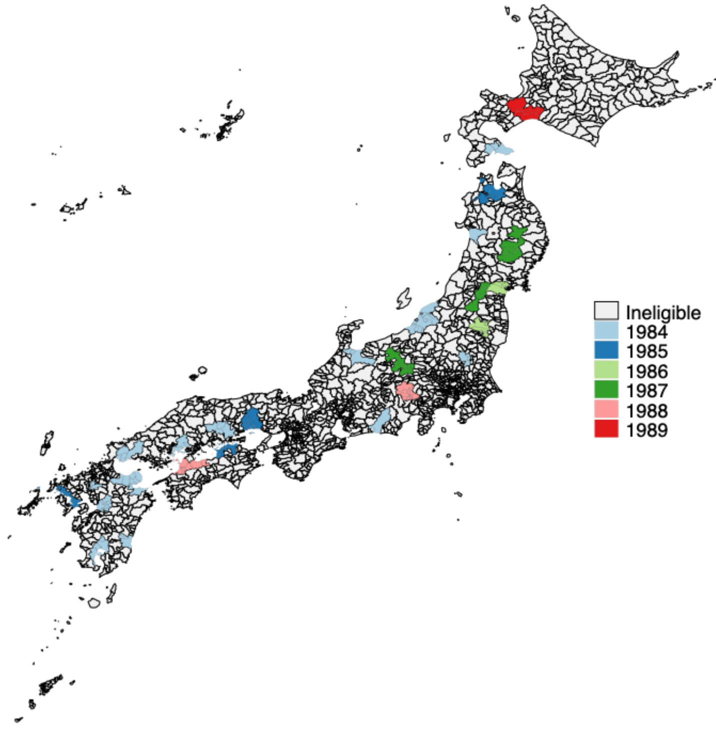
In 1988, the Japanese government passed a second regional policy program, called Intelligent Location (*zunō ritti*), which offered similar bonus depreciation incentives to firms in industries engaged in high-tech services such as software and telecommunications. The goal of this second policy wave was to build up the intermediate goods network in the clusters created by Technopolis, while also expanding the catchment areas for these clusters. Among the 26 Technopolis clusters, 15 regions were also designated Intelligent Locations. Figure 2 shows that the new Intelligent Locations were adjacent to the existing Technopolis sites. In total, 319 municipalities were included in Intelligent Locations, and of these, 244 were not previously eligible under Technopolis; 45 became eligible in 1989, 133 in 1990, 45 in 1991, 58 in 1992, and 38 in 1994.

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

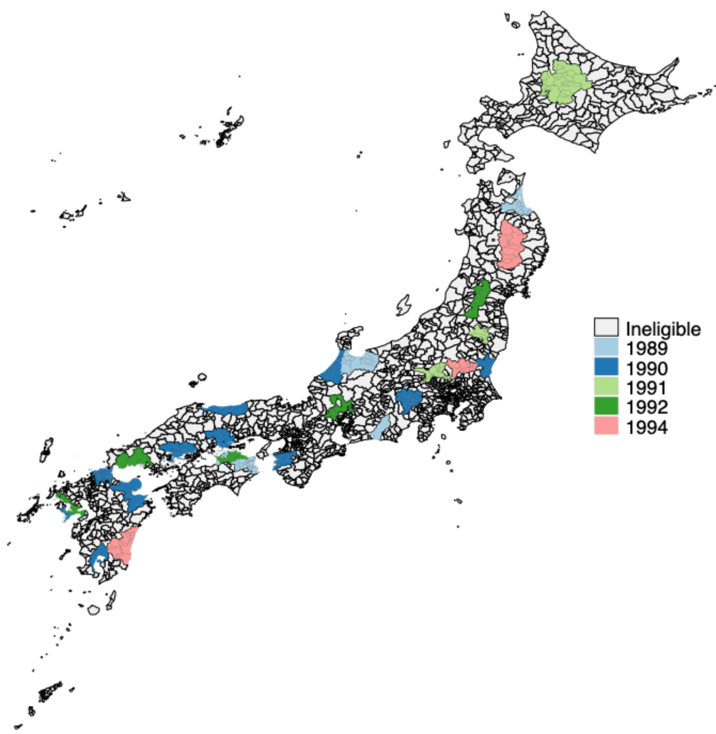
[9] While we do not observe the registered address for parent firms in our plant-level Census data, in future work we will explore whether listed firms headquartered in Tokyo – for which we do observe the registered address – were more likely to relocate resources under the Intelligent Location policy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

FIGURE 2. Map of Areas Eligible for Bonus Depreciation

A. Technopolis Policy



B. Intelligent Location Policy



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

How economically distinct were the sites selected by the Technopolis and Intelligent Location policies? Table 3 compares local macroeconomic characteristics of policy sites to non-policy sites in 1980, prior to the implementation of Technopolis. Policy sites have more manufacturing employment and establishments, with a larger capital stock than their ineligible counterparts. While eligible areas are more populated on average than the universe of ineligible locations, they have similar per capita income and growth rates in plants and CRE prices. The main difference is in terms of property values. The average median price per square meter for commercial land is roughly one-third lower in eligible sites than in ineligible sites, and housing is also a slightly lower share of total household expenditures. Our empirical strategy differences out these *ex ante* discrepancies in the economic trajectory between eligible and ineligible sites by assigning treatment at the firm (or plant) level, which ultimately means comparing firms with otherwise similar balance sheets located in the same area but with different eligibility status due to their industry.

3 Multi-plant Firm Data

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

3.1 Census of Manufactures

Our main dataset consists of the plant-level microdata from the the Census of Manufactures (COM, or *kōgyō tōkei chōsa* in Japanese) conducted by Ministry of Economy, Trade and Industry (METI) for each year from 1980 to 2000. In years ending in 0,3,5, and 8 (e.g. 1980, 1983, 1985, 1988) our data include all plants in the manufacturing sector regardless of size. However, in other survey years, METI only maintains microdata files for plants with four full-time employees or more, which excludes sole proprietorships. To form a balanced panel, we restrict our sample to all plants with four or more employees for which we have continuous annual survey responses. The COM data are valuable for studying responses to the Technopolis and Intelligent Policy initiatives given the findings in the corporate finance literature that 1) immediate cash flows from bonus depreciation help offset the large fixed costs of purchasing key production inputs (Zwick & Mahon 2017), and 2) financing constraints are more prevalent for very small firms who tend to rely on pledging physical collateral to obtain bank loans (e.g. Hadlock & Pierce 2010; Bahaj, Foulis, & Pinter 2020).

In terms of variable coverage, the COM survey asks plants to report a snapshot of their basic operations within the survey year, including full-time and part-time employment, the total wage bill, inventory, and cost of intermediate goods used in production. Key to our analysis are the variables pertaining to physical capital investment such as the book value of properties, plants, and equipment (PPE), which can be decomposed into three categories: machines, land, and buildings. It is standard in the corporate finance literature to define investment as the year-on-year change in net book value of PPE plus accounting depreciation. Unfortunately depreciation is not separately

TABLE 3. Economic Characteristics of Eligible vs. Ineligible Locations

	Technopolis				Intelligent City			
	Eligible		*Ineligible*		*Eligible*		*Ineligible*	
	Mean (s.d.)	[min,max]	Mean (s.d.)	[min,max]	Mean (s.d.)	[min,max]	Mean (s.d.)	[min,max]
Total mfg. employment	9,524 (13,887)	[136, 109,649]	5,706 (23,648)	[0, 723,990]	6,466 (11,999)	[34, 109,649]	5,919 (24,873)	[0, 723,990]
Heavy industry employment share	0.175 (0.128)	[0.025, 0.516]	0.212 (0.150)	[0.013, 0.875]	0.178 (0.127)	[0.025, 0.516]	0.214 (0.152)	[0.013, 0.875]
Establishments w/> 4 employees	370 (576)	[10, 4,769]	241 (1,389)	[1, 47,196]	246 (445)	[3, 4,769]	252 (1,472)	[1, 47,196]
Mfg. plant capital stock	3,527 (7,190)	[0, 5,961]	1,620 (4,605)	[0, 7,570]	2,334 (6,571)	[0, 7,570]	1,650 (4,416)	[0, 5,687]
Per capita income	556 (104)	[292, 764]	553 (158)	[196, 1,446]	536 (115)	[229, 803]	557 (162)	[196, 1,446]
Census population	119,885 (186,727)	[4,824, 1,401,757]	64,110 (279,303)	[225, 8,351,856]	75,536 (159,918)	[1,360, 2,153,666]	67,122 (293,185)	[225, 8,351,856]
Population > 65 y.o.	11,439 (14,653)	[568, 87,440]	5,783 (22,151)	[27, 686,436]	7,339 (13,063)	[178, 167,476]	5,997 (23,213)	[27, 686,436]
Median price/m^2 for CRE	63.93 (35.83)	[6.60, 180.00]	100.91 (95.33)	[6.35, 571.00]	66.22 (41.65)	[6.60, 180.00]	103.16 (97.50)	[6.35, 571.00]
Housing expenditure share	0.091 (0.024)	[0.027, 0.141]	0.096 (0.036)	[0.028, 0.241]	0.084 (0.023)	[0.027, 0.141]	0.100 (0.037)	[0.028, 0.241]
$\%\Delta^{1980-83}$ mfg. employment	9.8 (20.7)	[−32.0, 136.6]	6.3 (20.8)	[−100, 219.1]	6.8 (19.2)	[−100, 136.6]	6.5 (21.2)	[−100, 219.1]
$\%\Delta^{1980-83}$ establishments	7.1 (12.0)	[−12.5, 72,7]	6.4 (18.6)	[−72.7, 200.0]	6.1 (13.8)	[−66.7, 87.5]	6.5 (19.0)	[−72.7, 200.0]
$\%\Delta^{1980-83}$ CRE price/m^2	57.7 (40.1)	[10.3, 203]	69.8 (64.1)	[−37.1, 722.5]	62.9 (46.0)	[−9.2, 276.1]	69.5 (64.7)	[−37.1, 722.5]
# of municipalities	141		1,568		319		1,390	

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

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.

3.2 DBJ Corporate Balance Sheet Data

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

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

Although location information is not directly available in the DBJ database, we obtain a snapshot of corporate geography in the pre-reform period by merging in the hand-collected data on listed firms' locations constructed by LaPoint (2020). Registered and production HQ locations are reported by the firm on the cover page of their annual securities filings – equivalent to the Form 10-K in the U.S. (known as the *yuhō* in Japanese) – and firms are required to report the municipality of any operating locations, regardless of whether the property is owned or rented.[11] Firms also allocate employees and book values of owned buildings and land to each facility reported in this section of their filings, which allows us to compare some plant-level outcomes before and

[10]In future work, to track plants over the course of the early 1980s when Technopolis was first activated, we plan to backfill the panel using the plant master database (*kōgyō tōkei* converter) prepared and disclosed by the Research Institute of Economy, Trade and Industry (RIETI). Similarly, we use the Firm Master database (*kigyō* master) prepared by METI and the "Basic Survey of Japanese Business Structure and Activity" to construct consistent firm panel ids. This is the approach used in Bernard & Okubo (2015).

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

after the reform.[12]

We match COM plants to their parent DBJ firms for the years 1986 – 2000 based on a fuzzy merge on the Japanese name of the parent firm in 1997 (the first year for which the name string is available in COM). We make two sample restrictions to ensure that firms in the DBJ sample can be matched to the COM data:

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

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

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

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

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

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

Table 4 reports firm and plant-level 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 (CAPEX). 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.

4 Empirical Strategy

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

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

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

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

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

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

TABLE 4. Summary Statistics for Multi-plant Firms

	Full DBJ Sample				Matched DBJ-COM Sample			
	Mean	Median	10th pct.	90th pct.	Mean	Median	10th pct.	90th pct.
Construction in progress	0.02	0.01	0.00	0.11	0.03	0.01	0.00	0.11
Non-real estate assets	0.83	0.44	0.02	2.26	1.07	0.74	0.07	2.76
Real estate assets	0.64	0.33	0.07	1.91	0.72	0.47	0.11	1.74
PPE	1.61	0.93	0.17	4.18	1.90	1.37	0.28	4.31
CAPEX	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. CAPEX is YOY change in the net book value of PPE plus accounting depreciation, scaled by total book assets at baseline. Long-term debt issues is defined as the YOY change in long-term loans payable, scaled by total book assets at baseline. Cash flow is net income less taxes paid. EBITDA is computed as operating income plus depreciation and amortization, and OCF is computed using the identity presented in Lian & Ma (2021). Bonus depreciation is net income from claiming bonus depreciation. $\mathbb{1}\{bonus > 0\}$ is a dummy equal to one in firm-years with strictly positive net income from bonus depreciation. We tabulate the total number of manufacturing plants firms list on their 1980 securities filings (i.e. the "Condition of Facilities" section of their *yuhō*).

(i) **Firm j level.** Based on the facility locations reported in its 1980 *yuhō* the firm controls one plant located in an eligible Technopolis area.[14]

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

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

Applying these criteria implies the decomposition of $Treatment_{j,k,t} = Treated_{j,k} \times Post_{j,t}$. In cases such as the three-plant example where one plant is eligible in 1984 and another in 1986, we set $Post_{j,t} = 1$ if $t \geq 1984$, and $Treated_{j,k} = 1$ if the firm is in an eligible industry. In sum, our DD model in (4.1) is a staggered DD where several potential within-firm treatments are stacked up via $Post_{j,t}$.[15]

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. Given the strong overlap between Intelligent Cities and Technopolis, we argue that even the Technopolis areas formed earlier in the 1980s would have continued to be partially treated under Intelligent Cities, even though the industry composition of treated firms may have differed between the 1980s and 1990s. This consideration motivates our use of staggered difference-in-differences research designs at different levels of treatment assignment.

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. 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

[14]We do not require the firm to own either the building or land to satisfy this criterion. However, given that CRE space in Technopolis areas is far less expensive than in ineligible areas (see Table 3), the vast majority of firms own some property attached to plants in Technopolis areas. 99% of DBJ firms own some building or land among all the facilities itemized in 1980.

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

trends assumption for potential outcomes without treatment must hold, and there must be no anticipatory effects. To examine the validity of the parallel trends assumption, we apply the imputation estimator of Borusyak, Jaravel, & Spiess (2021) [hereafter, *BJS*], which is robust to treatment effect heterogeneity in this staggered rollout setting. Since new Technopolis sites were announced within the year prior to the implementation date, we allow for anticipation effects of up to one year in our reported DD estimates. We accommodate anticipation effects by shifting forward $\beta_t \rightarrow \beta_{t+1}$ in event study specification (4.2).[16]

Finally, we acknowledge that our estimates are intent-to-treat (ITT) in the sense that the DD models assess 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 average treatment effect (ATE). While we do not observe the precise provision in the tax code that allows firms to make their observed 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 8 p.p. in most specifications), which validates our proposed mechanism, and suggests we are, at least partially, identifying treatment effects of the policy.

5 Firm Employment & Investment Responses

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

5.1 City-level Evidence of Extensive Margin Responses

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

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

on employment and establishments.[17]

The event study analysis reveals a clear, but slow-moving gap in the evolution of employment and plant creation between Technopolis eligible cities and ineligible cities. For employment, this gap widens starting four years after the introduction of tax incentives ($\widehat{\beta_5}$). Ten years after the reform, employment is 13% higher in eligible sites, while the number of establishments is 6% higher. The fact that Technopolis was associated with growth in new plants points to the success of the policy at generating long-lasting investment in the targeted regions.[18]

Given the summary statistics in Section 2, it is clear that locations selected for the Technopolis and Intelligent Cities programs have a distinct local economic profile which is reflected in the strong pre-trend in the event study for employment. Technopolis was enacted in the background of one of the largest real estate booms in modern history, and eligible areas both started with lower commercial real estate (CRE) price levels and experienced more muted price growth during the 1980s. However, within-region, Technopolis sites were selected based on proximity to major research universities, which means they were more economically dynamic than neighboring cities. We attempt to control for trends related to the real estate boom by computing median price per square meter for CRE as of 1980. We find qualitatively similar effects on employment and extensive margin investment when we do so, but the standard errors blow up because our sample drops down to only 375 cities for which we have CRE appraisal data.[19] The ability to more precisely measure eligibility at the 4-digit industry × location level and difference out some of these local macro trends motivates our firm-level analysis in the next subsection.

5.2 Firm-level Analysis

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

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 applying the *BJS* estimator for staggered DD designs. Figure 4 plots the dynamic effects $\widehat{\beta_t}$ of Technopolis eligbility for our six main outcomes of interest: the probability a firm claims bonus depreciation, cash flow (defined as net income before depreciation, after taxes paid), employment, construction in progress, the

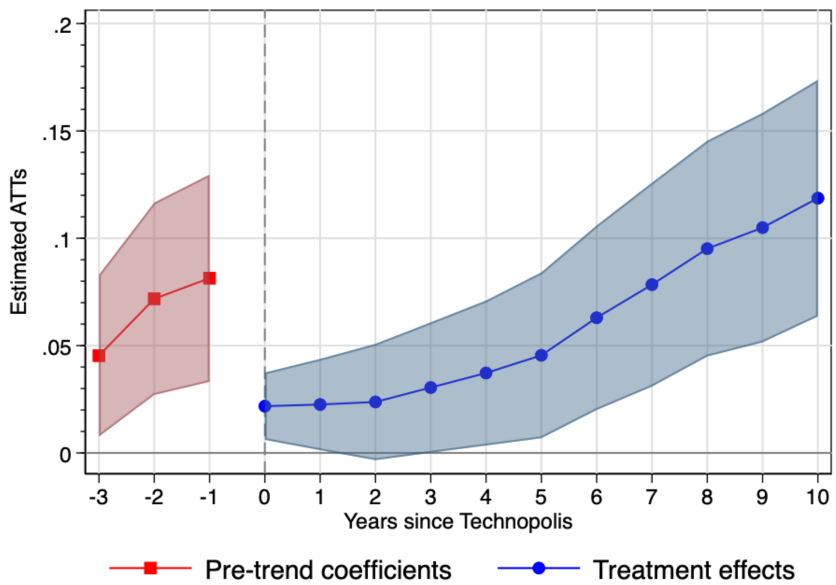
[17] To construct this city × 2-digit industry panel, we crosswalk the 2-digit manufacturing codes across the historical systems instituted in 1980, 1985, 2002, and 2008.

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

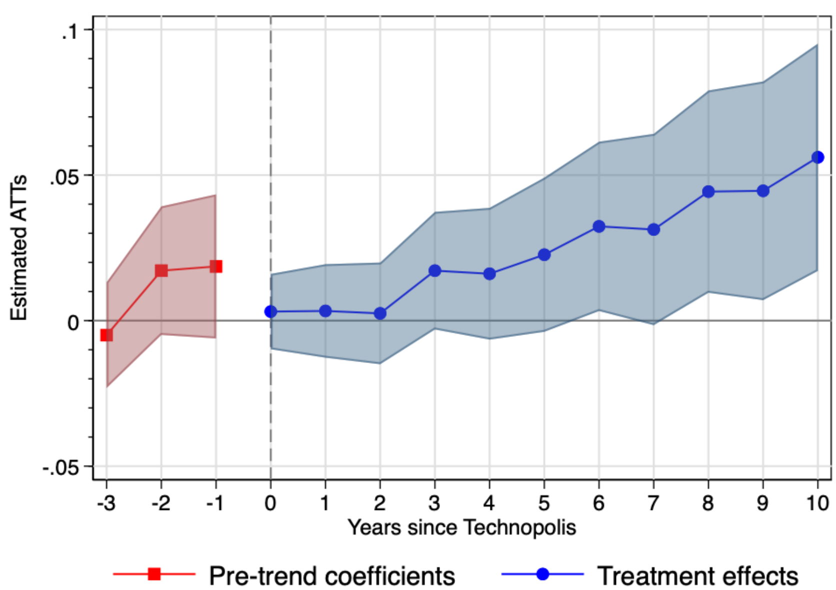
[19] See LaPoint (2020) for details on the appraisal data.

FIGURE 3. Dynamic City-level Responses to Technopolis Eligibility

A. Employment



B. Number of establishments



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

gross book value of non-real estate assets (including precision tools + machinery + vehicles), and long-term debt issuance (the YOY increase in long-term loans payable). All event studies feature one-year leads on the β_t coefficients to capture one-year anticipatory effects, although we do not lead the coefficients to conduct our pre-trends testing in what follows.

We focus on bonus depreciation claiming on the extensive margin given that 77% of firm-years feature zero net income from bonus depreciation. We deflate monetary variables by the value for that firm in the filing year before our sample starts (1975). Hence, the effects are scaled so that $\widehat{\beta_t}$ captures the growth in a monetary variable relative to the pre-sample baseline that can be attributed to the firm becoming eligible for Technopolis bonus claims.[20]

The first panel in Figure 4 shows the first stage of our research design by plotting how take-up of bonus depreciation incentives varies with respect to Technopolis eligibility. The propensity of eligible firms to increase their bonus claims steadily rises after the implementation date, with the effect peaking at 8.7 p.p. five years after enactment. Five years corresponds to a kink point in the tax schedule (Table 1), since firms can maximize their bonus rate if they invest within five years of the designated Technopolis area. While there is visual evidence of a pre-trend (with the one-year anticipation), when we test for pre-trends by running a separate regression using non-treated observations, we obtain a p-value of 0.694 on the hypothesis of joint significance of the loadings on the six lags. The second panel shows that income from bonus claims begins to show up in firm cash flows several years into the Technopolis period, peaking 8 years after eligibility.

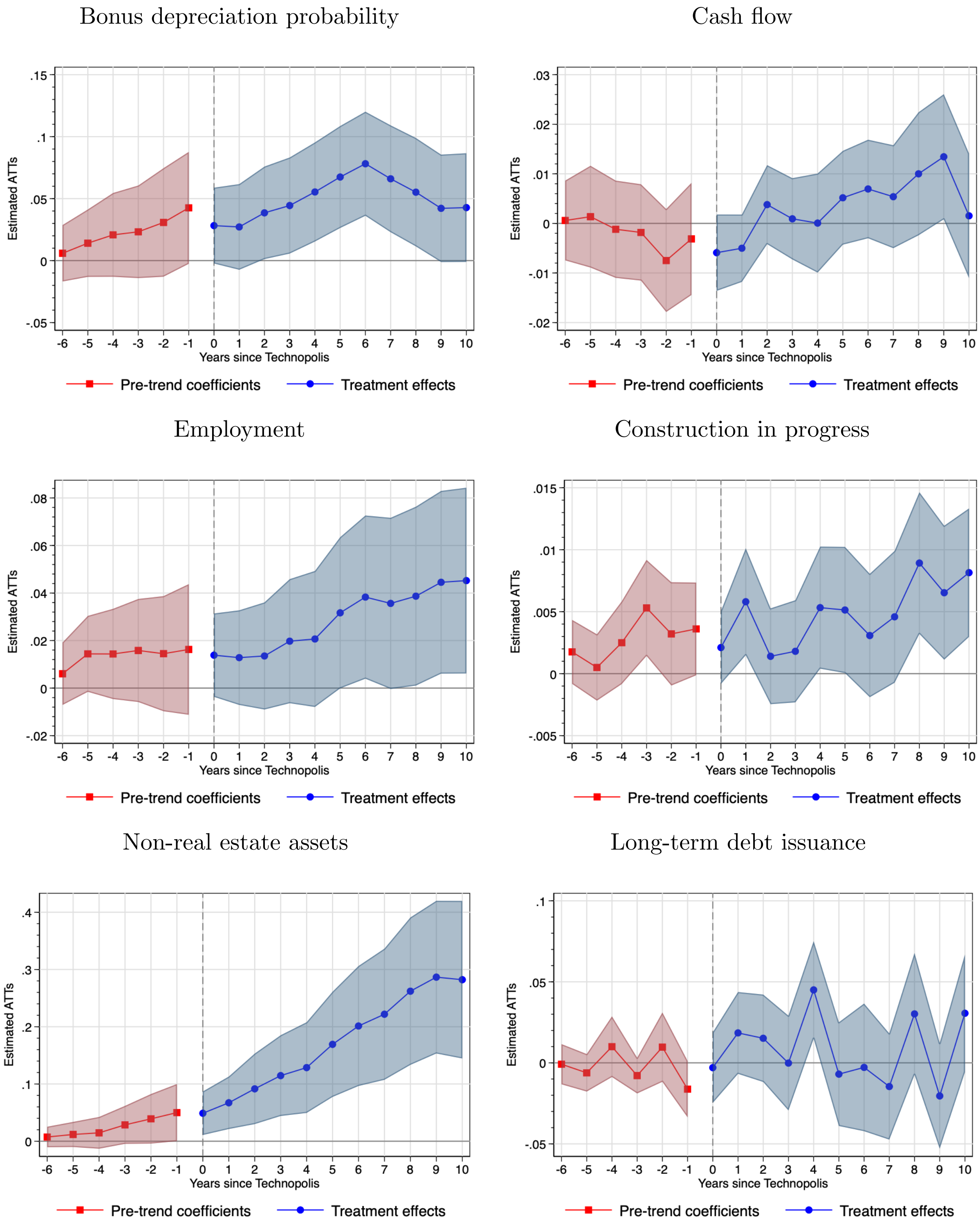
Overall employment rises at treated firms by 5% relative to the level at the sample start date about 5 years into the reform, and the effect plateaus thereafter. We also find a clear upward trend in outlays for construction in progress, although due to the lumpiness of investment and frequent revision of construction costs for projects, these dynamic effects are volatile. Recall that while the Technopolis bonus rates for real estate investment are half those for non-real estate tangible investment, buildings are much longer-lived assets, and therefore offer a larger immediate cash flow benefit. The gross book value 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. Debt issuance spikes three years into the Technopolis regime, but like construction in progress, debt issuance is lumpy because firms do not continuously draw down on existing credit lines with their main bank.[21]

The investment responses in Figure 4 are economically sizeable. The peak effect of Technopolis eligibility on non-real estate assets is 0.28 which is 27% of the standard deviation of gross book non-real estate assets. Similarly, for construction, the effect peaks at 0.009 which is 24% of the

[20] 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.

[21] The p-values on the pre-trends tests for the other outcomes we consider in Figure 4 are 0.731 for cash flow, 0.313 for employment, 0.099 for construction, 0.204 for non-real estate assets, and 0.311 for long-term debt issues.

FIGURE 4. Dynamic Firm Responses to Technopolis Eligibility



Notes: Each panel shows the dynamic response of an outcome of interest estimated via the staggered DD model in equation (4.2) using the imputation estimator method of Borusyak, Jaravel, & Spiess (2021). Each regression includes 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.

standard deviation of construction in progress. Importantly, while purchases of many types of non-real estate assets are reversible local investments, to the extent that the parent firm can sell or easily transport machines and other equipment away from the treated plant, construction of new structures or adding onto existing ones is not a reversible expense (at least not in the short-run). Technopolis was therefore successful relative to place-based tax breaks like the recent Foxconn Wisconsin case study in our Introduction at incentivizing firms not to “toe dip.”

Table 5 establishes the robustness of our results to the inclusion of a battery of controls for time-invariant firm characteristics interacted with year fixed effects, other common cash flow measures such as EBITDA and operating cash flow (OCF), and Tobin’s Q.[22] 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 controls for cash flows and region, size, and age-specific trends.

Comparing the point estimates in Panel B of Table 5 from estimating model (4.1) by OLS vs. the *BJS* estimator demonstrates the role that treatment effect heterogeneity plays in our setting. We find a 18.4 log points effect on construction outlays when we use OLS to estimate the staggered DD model, but a 24.2 log points effect when we estimate the same model via *BJS*. The difference between the estimators is even more stark with the inclusion of the time-varying controls for cash flow measures and the Q ratio. For instance, we find a statistically insignificant effect on construction of 9.3 log points when we include our time-varying controls and estimate via OLS (column 1), but instead find a significant 15.5 log points effect (p-value = 0.03) when we run the same model via *BJS*. 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. OCF includes cash flow from bonus claims, so it is mechanically related to the take-up behavior induced by Technopolis.[23]

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 upstream 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

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

[23]See Lian & Ma (2021) for a discussion on how to construct operating cash flow (OCF) and how it differs from EBITDA. For our purposes, the main distinction between the two cash flow measures is that net income from bonus depreciation write-offs will be reflected in OCF but not in EBITDA.

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

A. First stage: extensive margin bonus depreciation claims

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.085***	0.078***	0.078***	0.088***	0.081***	0.079***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
EBITDA		0.270***				
		(0.033)				
OCF		0.048***				
		(0.009)				
Q		−0.001				
		(0.002)				
Estimator	OLS	OLS	OLS	*BJS*	*BJS*	*BJS*
Firm FEs	✓	✓	✓	✓	✓	✓
Controls × year FEs			✓			✓
N	38,374	38,374	38,360	38,374	38,374	38,360
# Firms	1,508	1,508	1,507	1,508	1,508	1,507
Adj. R^2	0.536	0.541	0.552	0.536	0.541	0.552

B. Investment and employment responses

	Construction			Non-RE assets			Employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	0.093	0.184**	0.242***	0.154***	0.195***	0.192***	0.050*	0.082***	0.076**
	(0.067)	(0.077)	(0.078)	(0.043)	(0.050)	(0.049)	(0.029)	(0.032)	(0.034)
EBITDA	1.263***			0.559***			0.212***		
	(0.172)			(0.078)			(0.041)		
OCF	0.106			0.218***			0.118***		
	(0.074)			(0.022)			(0.012)		
Q	0.076***			0.038***			0.035***		
	(0.008)			(0.005)			(0.003)		
Estimator	OLS	OLS	*BJS*	OLS	OLS	*BJS*	OLS	OLS	*BJS*
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls × year FEs		✓	✓		✓	✓		✓	✓
N	26,996	26,985	26,985	36,396	36,383	36,383	38,340	38,326	38,326
# Firms	1,416	1,415	1,415	1,499	1,498	1,498	1,508	1,507	1,507
Adj. R^2	0.714	0.703	0.703	0.949	0.955	0.955	0.960	0.956	0.956

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. The outcome in Panel A is a dummy equal to one if the firm receives net income from bonus depreciation in a given year. In Panel B, construction is the log book value of construction in progress, non-RE assets is the log gross book value of PPE excluding buildings, land, and structures, and employment is the the log number of employees. Controls include static factors such as the size (by total assets), age measured from the Tokyo Stock Exchange listing date, and Census region of the HQ, all interacted with a full set of year dummies. EBITDA and OCF are defined using standard accounting principles. Q is the Q ratio, or the ratio of the market value of the firm (total assets + market equity - common equity - deferred tax payments relative to book assets). Standard errors clustered at the firm level are in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

TABLE 6. Local Spillovers of Technopolis via Untreated Firms

	Bonus claim		Construction		Non-RE assets		Employment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.094***	0.077***	0.156**	0.160**	0.169***	0.151***	0.088***	0.081**
	(0.030)	(0.029)	(0.078)	(0.079)	(0.050)	(0.050)	(0.033)	(0.032)
TreatedCity	0.030	−0.004	−0.090	−0.083	−0.118***	−0.150***	0.016	−0.004
	(0.017)	(0.017)	(0.068)	(0.070)	(0.034)	(0.037)	(0.016)	(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	0.536	0.552	0.703	0.703	0.949	0.950	0.955	0.956

Notes: The table shows results from estimating the spillover model in equation (5.1) at the firm level for our main outcomes of interest. Bonus claim is a dummy equal to one if the firm receives net income from bonus depreciation in a given year, construction is the log book value of construction in progress, non-RE assets is the log gross book value of PPE excluding buildings, land, and structures, and employment is the the log number of employees. Controls include static factors such as the size (by total assets), 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. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

augmented model which includes an additional term to isolate the effect of being located in an eligible area but not satisfying the industry criterion for bonus claims:

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

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

Table 6 provides results from estimating this spillover regression for our four main outcomes of interest: extensive margin bonus claiming, and the log of construction investment, non-real estate assets, 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 assets; firms in ineligible industries located in an active Technopolis site experienced a reduction in their non-real estate PPE of between 13% and 16%. 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 of a similar size and age. 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 early 1990s crash. This suggests Technopolis may have crowded out non-real estate physical investment among ineligible incumbent firms.

5.3 Heterogeneous Responses

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

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 Q-theory of investment – to rank firms based on their reliance on short-lived vs. long-lived assets.

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

The complete algorithm steps are described in LaPoint (2020), but we provide a brief outline here for convenience. The economic intuition underlying the approach is that a profit-maximizing firm will set the marginal rate of substitution between any two capital goods equal to the ratio of the goods' user costs. In addition to profit maximization, recovery of the capital input shares relies on two assumptions:

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

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

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

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 1975 – 1983.[24]

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

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

$$\begin{aligned} y_{j,t} = \gamma_j + \delta_t + \beta_1 \cdot Treatment_{j,t} \times LL - Firm_j \\ + \beta_2 \cdot Treatment_{j,t} \times SL - Firm_j + \eta' \cdot \mathbf{X}_{j,t} + \varepsilon_{j,t} \end{aligned} \tag{5.3}$$

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

[24]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.

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.[25] Hence, an alternative would be to lump buildings and machines into one category of long-lived assets, and group the remaining CAPEX 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 life. For example, within the machines category depreciation lives vary between 3 years for electricity boards used in the textile dyeing industry to 25 years for starch processing machines used in the agricultural industry.

Table 7 provides evidence in favor of the notion that long-lived asset firms were more likely to claim and use bonus cash flows under the Technopolis regime. The first column shows bonus claim probability increased by 9 p.p. for long-lived asset firms, but not at all for short-lived asset firms. Firms relying more on properties also employed more workers in response to Technopolis eligibility. On the other hand, the difference between $\widehat{\beta}_1$ and $\widehat{\beta}_2$ in equation (5.2) 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 0.47 in each subgroup.[26]

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

[26] We also checked whether a simple above/below median split inherent in equation (5.2) is masking non-linear effects across the distribution of ω_{build}. We uncover a U-shaped pattern when we re-estimate versions of (5.2) where we interact $Treatment_{j,t}$ with dummies indicating the quintile of ω_{build}. For example, bonus claiming probability increases by 16 p.p. for firms in the bottom quintile with $\omega_{build} < 0.27$, and by 15 p.p. for firms in the top quintile, with no statistically significant response in the middle of the building share distribution.

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

	Bonus claim		Construction		Non-RE assets		Employment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treatment \times LL-Firm$	0.090***	0.077***	0.177**	0.179**	0.183***	0.174***	0.082**	0.079**
	(0.030)	(0.030)	(0.078)	(0.079)	(0.052)	(0.052)	(0.034)	(0.033)
$Treatment \times SL-Firm$	−0.008	0.029	0.190	0.180	0.242**	0.263***	−0.035	−0.002
	(0.102)	(0.107)	(0.253)	(0.266)	(0.097)	(0.094)	(0.111)	(0.105)
p-value on difference	0.354	0.666	0.958	0.998	0.582	0.404	0.312	0.462
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	0.534	0.551	0.702	0.702	0.948	0.948	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 assets is the log gross book value of PPE excluding buildings, land, and structures, and employment is the the log number of employees. Controls include static factors such as the size (by total assets), 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 B for details on how we construct capital input shares. Standard errors clustered at the firm level are in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

5.3.2 The Role of Financing Constraints

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

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

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

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.[27] 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 (2020) 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 battery of baseline characteristics interacted with year dummies in the vector $\mathbf{X}_{j,t}$.

The results in Table 8 show that our findings of economically significant investment and employment responses are indeed driven by financially constrained firms and not by unconstrained firms. Bonus depreciation claim probability increased by 13 p.p. for constrained firms after Technopolis eligibility kicked in, with a 23% increase in construction outlays, a 37% increase in non-real estate assets, and 16% increase in employment. In contrast, the loading on $Treatment \times NFC$ is never statisticallly significant across all four outcomes, and with the exception of construction is close to zero, regardless of whether we saturate the model with controls. While we cannot reject the null that $\widehat{\beta_1}$ and $\widehat{\beta_2}$ are equivalent for construction, we easily reject the null of differential employment responses across the two groups (p-value = 0.007). Overall, Table 8 suggests the cash flow benefit provided by the Technopolis policy was claimed more by financially constrained firms who used the funds to finance construction and non-real estate purchases and hire more employees.

[27] 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 is essentially no relation between financing constraints and these firm characteristics.

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

	Bonus claim		Construction		Non-RE assets		Employment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treatment \times FC$	0.132***	0.100***	0.208**	0.212**	0.319***	0.277***	0.147***	0.105***
	(0.039)	(0.038)	(0.091)	(0.095)	(0.050)	(0.052)	(0.037)	(0.037)
$Treatment \times NFC$	0.017	0.021	0.122	0.114	0.002	0.008	−0.026	0.000
	(0.041)	(0.042)	(0.125)	(0.129)	(0.085)	(0.084)	(0.054)	(0.056)
p-value on difference	0.040	0.164	0.560	0.536	0.001	0.005	0.007	0.112
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 assets is the log gross book value of PPE excluding buildings, land, and structures, and employment is the the log number of employees. Controls include static factors such as the size (by total assets), 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. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

5.4 Matched Plant-Parent Firm Analysis

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

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

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

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

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

Under this approach, we find that roughly 13% of the plant-year observations in our matched sample covering 1980 and 1986–2000 are located in a Technopolis eligible area.[28] The number of manufacturing plants in our sample grows from 3,470 in 1980 (from the *yuhō*) to 5,639 in 2000, and peaks at 6,339 plants surveyed in 1997.

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

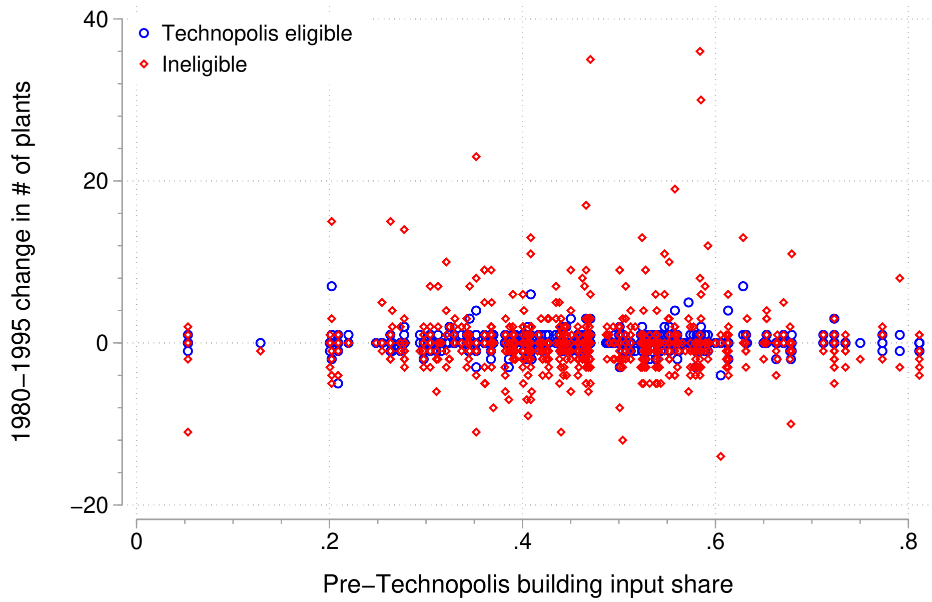
Figure 5 and Figure 6 provide visual evidence in favor of the narrative that ineligible areas captured much of the investment intended for plants in eligible areas. Figure 5 separately computes the change in the total number of eligible (blue) and ineligible plants (red) for each firm and plots these changes in plants against ω_{build}, which can vary between 0 and 1. In cases where a firm has both eligible and ineligible plants, then it will appear twice on the plot. Figure 6 conducts the same exercise except the y-axis is the total employment growth rate (Panel A) or the real book land asset growth rate across all plants in each bucket. To compute real book land asset growth, we deflate the book value of land reported by each plant by the city-level repeat appraisal index for CRE properties in that year compiled by LaPoint (2020). Technopolis overlapped with a dramatic rise in land values, especially commercial land in the CBD, so deflating by the local price index helps isolate the real investment response from the mechanical effects of spatial differences in land price inflation. We compute growth over 1980 and 1995 to allow all Technopolis locations to become eligible – recall the last one was enacted in 1989 – and to allow construction projects begun during the initial Technopolis period to be completed.[29]

At the extensive margin of investment in Figure 5 we observe that there is a negligible, positive gradient (slope = 0.119) in the change in the number of plants and ω_{build} for eligible areas, and a negligible but slightly positive gradient for ineligible areas (slope = 0.004). The lack of any discernible relationship between new plant creation and the desirability of bonus claims in both types of areas suggests the bulk of the construction response we document in Section 5 comes from expansions of existing plants. In contrast, when we examine employment and real land asset growth

[28] 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.

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

FIGURE 5. 1980-1995 Growth in Number of Plants by Technopolis Eligibility



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

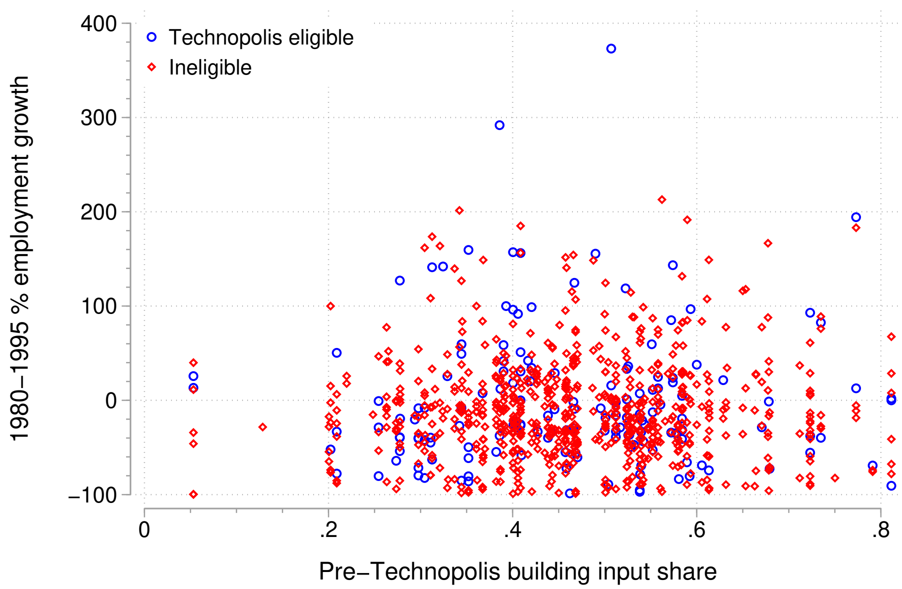
in Figure 6, there is a clear divergence between eligible and ineligible areas. For employment growth rates the gradient is 1.918 in eligible areas, and 9.056 in ineligible areas; for real land value growth rates the gradient is -8.560 in eligible areas, but the gradient flips sign to 3.584 in ineligible areas.

This evidence points to much of the gains in firm-level hiring and investment we documented in our main results in Section 5.1 arising from firms allocating resources to ineligible sites.[30] Taken together, it appears our relatively large listed firms expanded existing plants in Technopolis eligible areas to capture the immediate cash flow benefits of bonus depreciation, and then funneled the resources to support other pre-existing plants in ineligible areas. Hence, while the place-based financial incentives offered by Technopolis promoted irreversible investment in areas outside the major metros, it is unclear whether these investments were to the direct benefit of local residents.

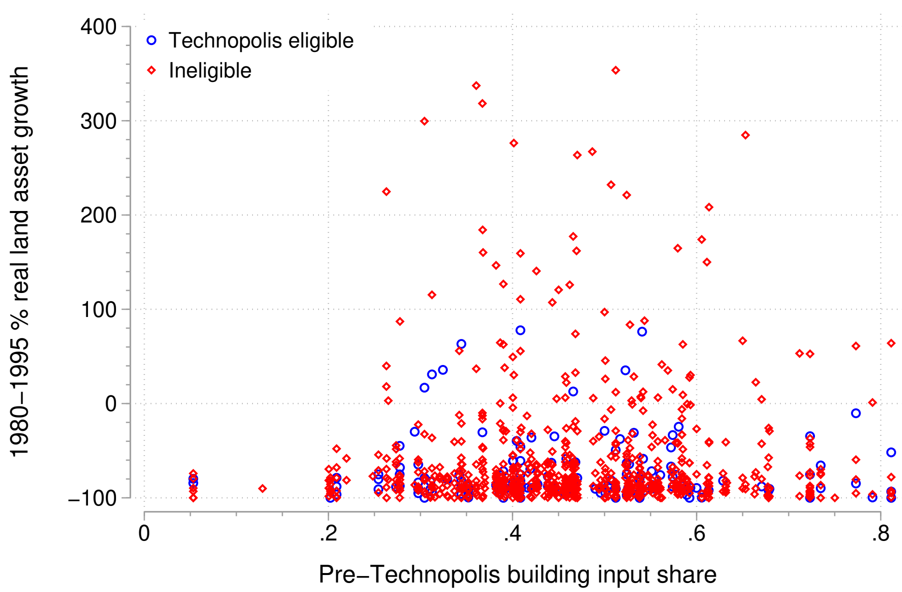
[30]While we observe other variables at the plant-level in COM such as acquisition of buildings and machines, at the moment we have no way to link these measures to the information reported at the plant level in the securities filings of our DBJ firms. In future work, we plan to expand the set of outcomes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

FIGURE 6. Employment Growth and Land Acquisitions by ω_{build}

A. 1980-1995 Employment growth



B. 1980-1995 Real land asset growth



Notes: In both panels, each point on the graph corresponds to a DBJ firm matched to the set of manufacturing plants it reported in the COM survey in 1995 and the manufacturing plants it reported in its securities filings in 1980. Points in red represent the 1980–1995 percentage growth rate in either the number of employees (Panel A) or the real acquisition value of land (Panel B) summing across all plants within the same firm located in a city not eligible for Technopolis. Points in blue represent the same statistics except computed over plants within the firm's network which are located in cities eligible for Technopolis. Therefore the same firm can appear twice on the plot. The x-axis variable is the firm-level building input share ω_{build} computed via the methods outlined in Section 5.3. To obtain real land values, we use the set of commercial real estate price indices constructed in LaPoint (2020). We winsorize growth rates at the 99th percentile.

6 Conclusion

We investigate the effects of place-based tax incentives on local investment, hiring, and firm location decisions using a series of regional policy experiments in 1980s and 1990s Japan as our laboratory. The Japanese government rolled out the Technopolis policy in a staggered fashion between 1984 and 1990, offering firms bonus depreciation rates as high as 30% towards tangible capital investment in economically peripheral regions. Much like the recent U.S. experience with Opportunity Zones enacted through the 2017 Tax Cuts and Jobs Act – which grant capital gains tax deferrals in exchange for a five-year investment in distressed neighborhoods – our setting features immediate financial incentives targeting firms in high-tech manufacturing industries with long-lived capital structures. Another important distinction of the bonus depreciation schedules offered by Technopolis is that they applied to investment in buildings, an asset class which has been ineligible for similar bonus depreciation episodes in the U.S. in 2001 and 2008.

Using a staggered difference-in-differences design, we find that multi-plant firms exercised these tax write-offs to increase their current cash flow by engaging in construction projects at locations within their internal network and investing in non-real estate assets such as machinery. Our estimated effects are economically large. A firm which became eligible to claim bonus depreciation on investments at one of its plant locations increased its outlays for construction by 0.24 standard deviations and increased its non-real estate assets by 0.27 standard deviations. Given the nature of these responses, we argue local bonus depreciation incentives are an effective way to promote immediate and irreversible corporate commitments to struggling regions in contexts where: (i) firms rely heavily on buildings in their production function, and (ii) bonus claims are attractive relative to existing accounting methods allowed under the tax code.

At the same time, we uncover mixed evidence that the place-based incentives accomplished their intended goal of promoting long-run growth in the catchment areas far away from the main metropolises. We find no evidence of positive spillovers to the control group of firms operating in eligible areas but which were ineligible for bonus claims due to their industry classification. While firm-level hiring increased by 13% after 10 years of the new policy regime, this response was apparently driven by firms hiring at sites where physical investment was not eligible for bonus claims. Future work will take our reduced-form estimates of firm responses to local tax incentives and examine the distributional consequences of place-based policy instruments through the lens of a structural model of multi-location firms using long-lived and short-lived capital.

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Online Appendix to

Place-Based Policies and the Geography of Corporate Investment

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

A 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 dies
	Machinists' precision tools, except powder metallurgy products
	Molds and dies, parts and accessories for metal products

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

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

B Details on Capital Input Share Calculations

In this appendix we offer some additional details on the perpetual inventory approach and nearest-neighbor matching algorithm outlined in Section 5.3 of the main text. Although a more detailed treatment of the perpetual inventory approach applied to the DBJ data can be found in LaPoint (2020), we emphasize aspects of the procedure that are specific to this paper.

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

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

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 (2020) to inflate book values of the real estate components of PPE (buildings + land). We then set $Pk_{i,t}k_{i,t}$ to this market value in the benchmark year of 1975; we truncate the investment series by setting $NOMI_{i,t}$ equal to the book value of assets i as of the end of the year prior to the benchmark year.

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

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

$$\theta^R_{i,t,t+1} = \theta_{t,t+1} \cdot \frac{(1-z_{i,t+1}) \cdot Pk_{i,t+1}}{(1-z_{i,t}) \cdot Pk_{i,t}} \tag{B.3}$$

Equation (B.3) refers to the asset-specific real discount factor from t to $t+1$, which is obtained by adjusting the nominal overall discount factor $\theta_{t,t+1}$ 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 $\theta_{t,t+1} = 1/(1+WACC_t)$. We take $\mathbb{E}_t(\theta^R_{i,t,t+1})$ to be the average value of $\theta^R_{i,t,t+1}$ over the panel.

User costs in equation (B.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

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

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

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

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

where we include in the function $h(X_j)$ the following variables: dummies for eight broad industrial sectors (see Table B.1 for a complete description), total assets, and a quadratic in age. We select this parsimonious set of variables to predict the probability of having non-missing user costs because the missing values arise for firms in particular sub-industries, and for firms which may pay more or less taxes on each of the tax bases depending on their age and balance sheet size. We then take the fitted probability value from (B.5) as the propensity score, and compute for each firm j with missing ω_i the squared difference between its propensity score and the propensity score of all firms with non-missing ω_i. The firm $-j$ that has the smallest squared difference in propensity scores then becomes the donor. We donate all of the ω_i from firm $-j$ to firm j.

Table B.1 tabulates the average and standard deviation for each of the six capital input shares for firms sorted into one of eight industrial sectors, including: light manufacturing, heavy manufacturing, real estate, construction, transportation, electronics, non-transportation services, and agriculture. There are intuitive differences in the capital structure across sectors, which provides a sanity check on our nearest-neighbor matching and perpetual inventory approaches to recovering the input shares. For example, heavy manufacturing firms make the most use of machinery in their production, while electronics firms have the highest input share for tools and precision instruments. Unsurprisingly, the transportation sector has the highest input share for vehicles.

In inspecting the differences in physical capital structure for firms in distinct sectors, we underscore that these capital input shares are based on asset <u>ownership</u>, rather than renting. While a real estate and construction firm may have a lot of properties listed on its portfolio, many of these properties are partially leased from third parties. In additional most of the profits from leasing companies come from rental income and management of properties. In contrast, manufacturing firms are more likely to have 100% equity in their facilities, and so the building share is therefore highest for that subset of firms.

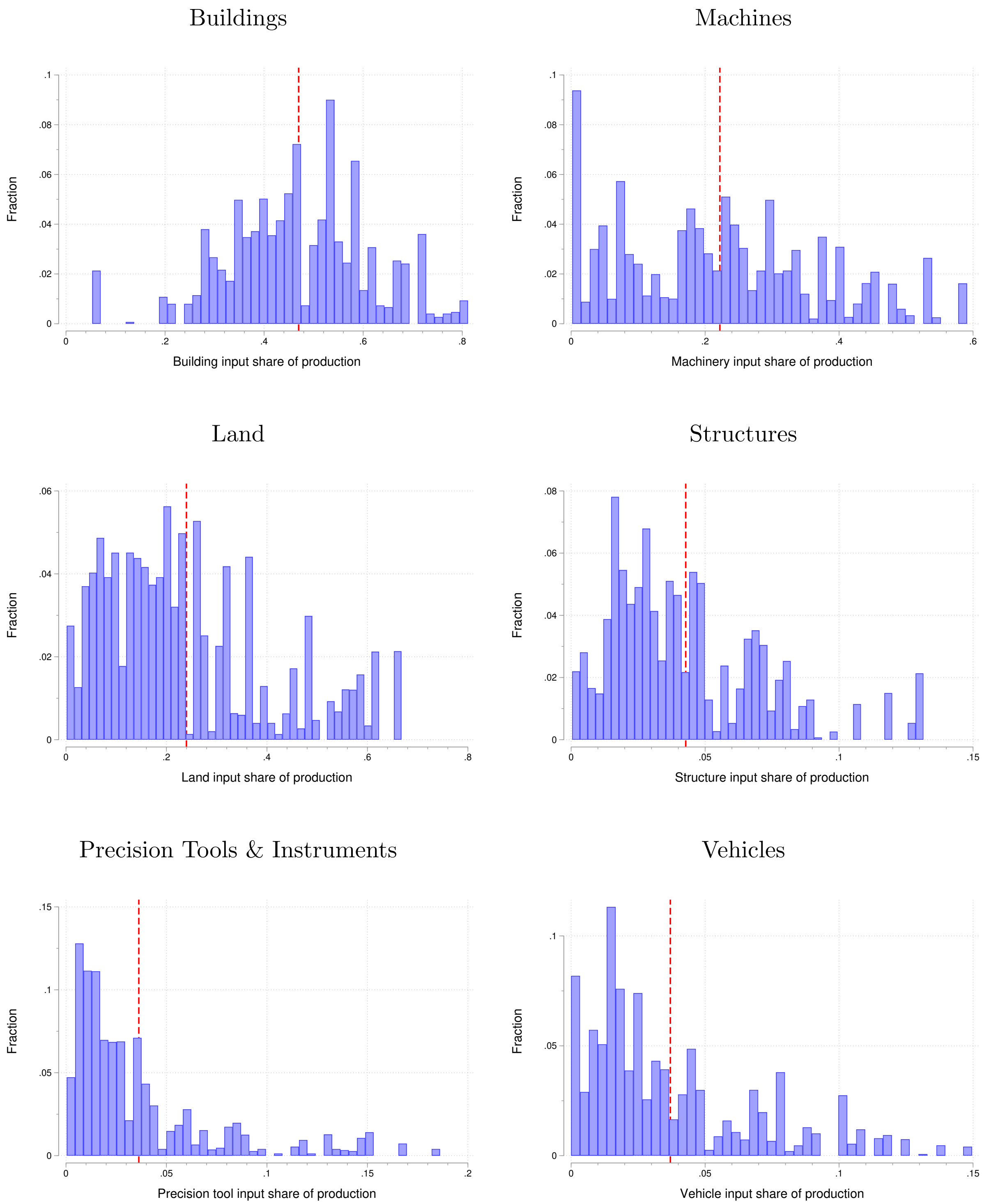
Figure B.1 plots the distribution of input shares for each capital type, after applying the nearest-neighbor matching. Dashed red lines indicate the average input share reported in Table B.1. Buildings account for an outsize share of production inputs for the majority of firms in our sample, with an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

Table B.1. Capital Input Shares by Type and Industrial Sector

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

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

FIGURE B.1. Distribution of Physical Capital Input Shares



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