Capital and Labor Reallocation Inside Firms*

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Abstract

We document how a plant-specific shock to investment opportunities at one plant of a firm ("treated plant") spills over to other plants of the same firm—but only if the firm is financially constrained. While the shock triggers an increase in investment and employment at the treated plant, this increase is offset by a decrease at other plants of the same magnitude, consistent with headquarters channeling scarce resources away from other plants and toward the treated plant. As a result of the resource reallocation, aggregate firm-wide productivity increases, suggesting that the reallocation is beneficial for the firm as a whole. We also show that—in order to provide the treated plant with scarce resources—headquarters does not uniformly "tax" all of the firm's other plants in the same way: It is more likely to take away resources from plants that are less productive, are not part of the firm's core industries, and are located far away from headquarters. We do not find any evidence of investment or employment spillovers at financially unconstrained firms.

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1 Introduction

When firms face binding financing constraints, headquarters can create value by actively reallocating scarce resources across projects. In particular, headquarters' control rights allow it to take away resources from some projects and allocate them to other, more deserving ones (Alchian, 1969; Williamson, 1975; Stein, 1997). Among other things, this implies an interdependence between otherwise unrelated projects:

> "Thus, for example, if a company owns two unrelated divisions A and B, and the appeal of investing in B suddenly increases, the argument would seem to imply that investment in A would decline—even if it is positive NPV at the margin—as corporate headquarters channels relatively more of its scarce resources toward B" (Stein, 1997, p. 112).[1]

This rationale for an internal capital market—based on the notion that headquarters channels scarce resources toward the most deserving projects—has implications for the boundaries of the firm. As Stein (1997) shows, it provides a plausible theory of optimal firm size and scope that is consistent with firms (not individual managers) owning the assets employed in the production process.[2] It has also implications for the design of a firm's internal organizational structure, as the fear of losing scarce resources may lead to managerial rent-seeking and, more generally, may distort managers' incentives (e.g., Milgrom, 1988; Milgrom and Roberts, 1988; Rajan, Servaes, and Zingales, 2000; Scharfstein and Stein, 2000; Brusco and Panunzi, 2004).

As the quote above illustrates, a key hypothesis of the efficient internal capital markets paradigm is that—when firms face binding financing constraints—an increase in the appeal of investing in one project should lead to a decline in investment in other projects. And yet, little is known about whether this hypothesis is true in the data. The paper

[1] Similarly, Shin and Stulz (1998, p. 543) define an internal capital market to be efficient if "its allocation of funds to a segment falls when other segments have better investment opportunities."

[2] A shortcoming of the Grossman-Hart-Moore property-rights paradigm (Grossman and Hart, 1986; Hart and Moore, 1990) is that it cannot explain why firms, as opposed to individual managers, own productive assets. See Bolton and Scharfstein (1998) and, especially, Holmström (1999) for a critique along these lines.

that perhaps comes closest to testing this hypothesis is Shin and Stulz (1998). Using Compustat segment data, the authors regress investment by a segment on the industry qs of the firm's other segments. They overwhelmingly reject that the qs of the other segments affect the segment's investment and conclude: "Unless one believes that firms face no costs of external finance, this evidence suggests that the internal capital market does not allocate resources efficiently" (Shin and Stulz, 1998, p. 544).

This paper takes a fresh look at the efficient internal capital markets hypothesis using plant-level data from the U.S. Census Bureau. We consider a "natural experiment" that is close in spirit to the thought experiment outlined in Stein's quote: Suppose the appeal of investing in one plant suddenly increases—does investment in other plants of the same firm decline? To obtain exogenous variation in the "sudden increase in the appeal of investing in one plant," we use the introduction of new airline routes that reduce the travel time between headquarters and plants. Giroud (2012) uses this source of variation to study whether proximity to headquarters affects plant-level investment. The idea is that a reduction in travel time makes it easier for headquarters to monitor a plant, thereby making investment in the (treated) plant more appealing.[3,4]

In this paper, we use the "sudden increase in the appeal of investing in one plant" as our starting point and examine whether it leads to a reallocation of resources within the firm, whether headquarters—in order to provide the treated plant with resources—"taxes" some plants more than others, and whether the reallocation is beneficial for the

[3] The motivation for using travel time instead of geographical proximity is that the former entails plausibly exogenous variation. Furthermore, it constitutes a more direct proxy for the ease of monitoring: A plant may be located far away from headquarters, yet monitoring may be easy, because there exists a short direct flight. Conversely, a plant may be located in the same state as headquarters, yet monitoring may be costly, because it involves a long and tedious trip by car.

[4] Anecdotal evidence that proximity matters for monitoring abounds. For example, Ray Kroc, founder of McDonald's, writes in his autobiography: "One thing I liked about that house was that it was perched on a hill looking down on a McDonald's store on the main thoroughfare. I could pick up a pair of binoculars and watch business in that store from my living room window. It drove the manager crazy when I told him about it. But he sure had one hell of a hard-working crew" (Kroc, 1992, p. 141). For anecdotal evidence that top-level managers consider traveling to plants important, see the following quote from *Chief Executive* magazine (October 1, 2003): "Lillie considers travel from headquarters to see a company's other plants or offices a must. "You need to see it, feel it, touch it, taste it before you make a good decision," says Lillie." (James Lillie is the current CEO and former COO of Jarden, a Fortune 500 company based in Rye, N.Y., with over 23,000 employees.)

firm as a whole, as argued by the internal capital markets hypothesis.

For financially constrained firms, we find that investment and employment both increase at the treated plant, while they both decline at other plants of the same firm. Moreover, the increase at the treated plant is of the same order of magnitude as the decline at the other plants: At the treated plant, investment (employment) increases by $186,000 (five employees), while it declines by $179,000 (six employees) at all other plants together.[5] In contrast, for financially unconstrained firms, we find no evidence of investment or employment spillovers across plants.[6] Overall, this evidence suggests that headquarters channels resources away from other plants and toward the treated plant—but only if the firm is financially constrained.

When we investigate the dynamics of the treatment effect, we find that, for financially constrained firms, the increase in investment and employment at the treated plant occurs around the same time as the decline at other plants, namely, about one year after the treatment. This is reassuring, for two reasons. First, that the effect occurs with a lag of about one year suggests that there are no existing pre-trends in the data. Second, that the timing between the treated plant and the other plants coincides so well provides further evidence that headquarters channels scarce resources away from other plants and toward the treated plant.

While our results suggest that headquarters takes away resources from other plants, the *average* spillover effect is relatively small. There are several reasons for this. First, the amount of resources needed to "feed" the treated plant—and thus the amount that must

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[5]This points to an interesting potential "dark side" of internal labor markets. (See Tate and Yang (2011) for a "bright side.") Unless workers are transferred across plants—which is less likely if the treated and the other plants are located far away from one another—our results suggest that the treated plant hires new workers while some of the other plants are forced to lay off workers. Hence, some workers are laid off not because their plant is doing poorly, but because some other plant within the same firm is doing relatively better. While this is speculative, this additional layoff risk due to headquarters engaging in "winner-picking" could be an explanation for Schoar's (2002) finding that conglomerates pay higher wages on average.

[6]Looking at financially unconstrained firms provides us with a useful falsification (or placebo) test. Specifically, not finding any spillovers at financially unconstrained firms suggests that the introduction of a new airline route between headquarters and the treated plant has *no direct effect* on other plants of the same firm, suggesting that the decline in investment and employment at other plants of financially *constrained* firms is due to headquarters reallocating scarce resources and not, e.g., because the other plants' investment opportunities have suffered.

be taken away from other plants—is fairly modest. Second, this amount is divided among many other plants, implying that the *average* amount taken away from any individual plant is relatively small. Indeed, when we focus on firms that have only few other plants, the spillover effect becomes much stronger. Also, the average spillover effect is quite noisy, as headquarters does not uniformly "tax" all of the firm's other plants in the same way. While some plants may experience a large drop in their resources, others may experience none. To address this issue, we examine which other plants are primarily affected by the resource reallocation. We find that headquarters is more likely to take away resources from plants that are less productive, are not part of the firm's core industries, and are located far away from headquarters. When we focus on those other plants, we find again that the spillover effect becomes much stronger.

We finally examine the aggregate (or net) effect at the firm level. For financially constrained firms, we find that the aggregate effect on investment and employment at the firm level is zero, consistent with our previous result showing that the increase in investment and employment at the treated plant is offset by a decrease at other plants of the same magnitude. In contrast, for financially unconstrained firms, the aggregate effect on investment and employment is positive. Given that these firms exhibit no (negative) spillovers, this is indeed what one would expect.

A key premise of the efficient internal capital markets paradigm is that the resource reallocation is beneficial: While resources may be taken away from projects that are positive NPV at the margin, they are channeled toward other projects whose investment prospects are *even* better. To investigate this hypothesis, we consider the aggregate effect on productivity at the firm level. Doing so also helps us distinguish the efficient internal capital markets hypothesis from alternative stories, e.g., the resource reallocation might be the outcome of lobbying by managers of the treated plant, who suddenly find it easier to lobby given that their travel time to headquarters is reduced. While such lobbying efforts can explain why the treated plant gains at the expense of other plants, they are unlikely to yield an increase in firm-wide productivity. Regardless of which productivity measure we use, we find that, for financially constrained firms, firm-wide productivity increases. For financially unconstrained firms, the firm-wide productivity increase is even higher, but this is not surprising, given that these firms are not forced to take resources away from plants that are positive NPV at the margin.

Aside from Shin and Stulz (1998), several papers examine whether segments within conglomerates are interdependent. Notably, Lamont (1997) shows that when oil prices decline, integrated oil companies cut investment across the board. In particular, they cut investment in non-oil segments. His conclusion is that the cut is the reversal of previous, wasteful overinvestment into these segments. While clearly related, Lamont's study and ours test different hypotheses. His study examines whether a cash-flow shock spills over to other segments *holding investment opportunities constant*. The hypothesis is that, following a negative cash-flow shock to one segment, investment should decline across all segments. In contrast, our hypothesis is that, following a plant-specific shock to investment opportunities, investment at the treated plant and other plants of the same firm should move in opposite directions.

Both Lamont (1997) and Shin and Stulz (1998) use Compustat segment data. By contrast, Maksimovic and Phillips (2002) construct segment-level data by aggregating plant-level data at the firm-industry level. They find that a segment's growth varies positively (negatively) with the other segments' productivity if the segment's change in shipments at the industry level is lower (higher) than that of the firm's median segment. As they argue, this is consistent with a neoclassical model of optimal firm size and growth. Lastly, Maksimovic and Phillips (2008) find that the negative effect of a segment's (predicted) financial dependence on acquisitions and (to a lesser extent also on) capital expenditures is greater for single-segment firms than it is for conglomerate segments, especially in growing and consolidating industries.

The remainder of this paper is organized as follows. Section 2 describes the data, empirical methodology, and summary statistics. Section 3.1 presents our main plant-level regressions. Section 3.2 examines which other plants are primarily affected by the resource reallocation. Section 3.3 examines the aggregate (or net) effect at the firm level. Section 4 offers concluding remarks. The Appendix describes how our measures of financing constraints are constructed.

2 Data

2.1 Data Sources and Sample Selection

A. Plant-Level Data

The plant-level data are obtained from three different data sets provided by the U.S. Census Bureau. The first data set is the Census of Manufactures (CMF). The CMF is conducted every five years ("Census years") and contains detailed information about all manufacturing plants in the U.S. with at least one paid employee. The second data set is the Annual Survey of Manufactures (ASM). The ASM is conducted in all non-Census years and covers a subset of the plants covered by the CMF: Plants with at least 250 employees are included in every ASM year, while plants with fewer employees are randomly selected every five years, where the probability of being selected is higher for relatively larger plants. Although the ASM is technically referred to as a "survey," reporting is mandatory, and fines are levied for misreporting. The CMF and ASM cover approximately 350,000 and 50,000 plants per year, respectively, and contain information about key plant-level variables, such as capital expenditures, total assets, value of shipments, material inputs, employment, industry, and location.

The third data set is the Longitudinal Business Database (LBD), which is compiled from the business register. The LBD is available annually and covers all business establishments in the U.S.—i.e., not only manufacturing plants—with at least one paid employee.[7] The LBD contains longitudinal establishment identifiers along with data on employment, payroll, industry, location, and corporate affiliation. We use the longitudinal establishment identifiers to construct longitudinal linkages between the CMF and ASM, allowing us to merge the two data sets into a single, longitudinal panel.

Information about headquarters is obtained from two additional data sets provided by the U.S. Census Bureau: the Auxiliary Establishment Survey (AES) and the Standard Statistical Establishment List (SSEL). The AES contains information about non-

[7] An establishment is a "single physical location where business is conducted" (Jarmin and Miranda, 2003, p. 15). Establishments are the economic units used in the Census data sets.

production ("auxiliary") establishments, including headquarters. The SSEL contains the names and addresses of all U.S. business establishments.

Our sample covers the period from 1977 to 2005. (1977 is the first available AES year; 2005 is the latest available ASM year.) To be included in our sample, we require that a plant has a minimum of two consecutive years of data. Following common practice in the literature (e.g., Foster, Haltiwanger, and Syverson, 2008), we exclude plants whose information is imputed from administrative records rather than directly collected. We also exclude plant-year observations for which employment is either zero or missing. Finally, to ensure that the physical distance between plants and headquarters is comparable across years, we exclude firms that change the location of their headquarters during the sample period. The results are virtually identical if we include these firms. These selection criteria leave us with an initial sample of 1,332,824 plant-year observations.

B. Airline Data

The data on airline routes are obtained from the T-100 Domestic Segment Database (for the period 1990 to 2005) and from ER-586 Service Segment Data (for the period 1977 to 1989), which are compiled from Form 41 of the U.S. Department of Transportation (DOT).[8] All airlines that operate flights in the U.S. are required by law to file Form 41 with the DOT and are subject to fines for misreporting. Importantly, the T-100 and ER-586 are not samples; they include *all* flights that have taken place between any two airports in the U.S.

The T-100 and ER-586 contain monthly data for each airline and route ("segment"). The data include the origin and destination airports, flight duration ("ramp-to-ramp time"), scheduled departures, performed departures, enplaned passengers, and aircraft type.

C. Financing Constraints

[8] The T-100 Domestic Segment Database is provided by the Bureau of Transportation Statistics. The annual files of the ER-586 Service Segment Data are maintained in the form of magnetic tapes at the U.S. National Archives and Records Administration (NARA). We obtained a copy of the tapes from NARA.

The data used to compute measures of firms' financing constraints are obtained from Compustat. We link Compustat to the CMF/ASM/LBD by using the Compustat-SSEL bridge maintained by the U.S. Census Bureau. Limiting ourselves to plants of publicly traded firms with a coverage in Compustat reduces our sample to 435,467 plant-year observations.

D. Additional Sample Selection Criteria

Given that we wish to provide a comprehensive picture of investment and employment spillovers within firms, we must focus on firms for which we have detailed information about all, or at least most, of the firms' plants. Since detailed plant-level data are only available for manufacturing plants, we therefore limit our sample to "pure" manufacturing firms. Specifically, we use the LBD to compute the total number of employees for each firm. (As mentioned previously, the LBD covers *all* U.S. business establishments.) We then limit our sample to those firms whose plants in the CMF/ASM account for at least 90% of the firm's total employees.[9] This additional selection criterion leaves us with a final sample of 291,358 plant-year observations, corresponding to 33,695 firm-year observations.

2.2 Definition of Variables and Empirical Methodology

The introduction of new airline routes that reduce the travel time between headquarters and plants makes it easier for headquarters to monitor plants. In this paper, we examine the effect of this "treatment" on the treated plant itself—i.e., the plant whose travel time to headquarters is reduced—on other plants belonging to the same firm as the treated plant, and on the firm as a whole. Theories of internal resource reallocation based on "winner-picking" (e.g., Stein, 1997) rest on the premise that firms face binding financing constraints. Accordingly, we examine the effect separately for financially constrained and unconstrained firms.

[9]Using a 90% (instead of a 100%) cutoff rule to classify "pure" manufacturing firms addresses two measurement issues. First, auxiliary establishments of manufacturing firms may be assigned non-manufacturing SIC codes in the LBD—e.g., warehouse facilities may be classified as SIC 4225 (general warehousing and storage)—even though their very purpose is to support manufacturing plants. Second, assigning industries to establishments is subject to potential measurement error.

A. Plant-Level Regressions

To examine the effect on the treated plant and on other plants of the same firm, we use a difference-in-differences approach. Specifically, we estimate:

$$y_{ijlt} = \alpha_i + \alpha_t + \alpha_l \times \alpha_t + \beta_1 \times \text{ treated}_{ijt} + \beta_2 \times \text{ other}_{ijt} + \boldsymbol{\gamma}'\mathbf{X}_{ijlt} + \varepsilon_{ijlt}, \qquad (1)$$

where i indexes plants, j indexes firms, l indexes plant location, t indexes years, y is the dependent variable, α_i and α_t are plant and year fixed effects, $\alpha_l \times \alpha_t$ are location times year fixed effects, "treated" is a dummy variable that equals one if a new airline route that reduces the travel time between plant i and its headquarters has been introduced by year t, "other" is a dummy variable that equals one if a plant belongs to the same firm as the treated plant and the "treated" dummy is set equal to one, and $\mathbf{X}$ is a vector of control variables. Location is defined at the Metropolitan Statistical Area (MSA) level.[10] The main coefficients of interest are β_1, which measures the effect of the introduction of the new airline route on the treated plant and, especially, β_2, which measures the effect on other plants within the same firm.

The dependent variables are investment and employment. Investment is capital expenditures divided by capital stock.[11] Employment is the logarithm of the number of employees. All dependent variables are measured at the plant level and are industry-adjusted by subtracting the industry median across all plants in a given 3-digit SIC industry and year. To mitigate the effect of outliers, we winsorize all dependent variables at the 2.5th and 97.5th percentiles of their empirical distributions. The control variables are plant size and age. Plant size is the logarithm of the total value of shipments of a plant, while plant age is the logarithm of one plus the number of years since the plant has been in the LBD. To account for serial and cross-sectional dependence across different plants within

[10] The MSA classification is only available for urban areas. For rural areas, we treat the rural part of each state as a separate region. There are 366 MSAs in the U.S. and 50 rural areas based on state boundaries. (The District of Columbia has no rural area.) For expositional simplicity, we refer to these 416 geographical units as "MSAs."

[11] Both capital expenditures and capital stock are expressed in 1997 dollars. Capital expenditures are deflated using the 4-digit SIC deflator from the NBER-CES Manufacturing Industry Database. Real capital stock is computed using the perpetual inventory formula.

the same firm, we cluster standard errors at the firm level. We obtain similar results if we cluster standard errors at the MSA level.

To examine whether the treatment effect is different for financially constrained and unconstrained firms, we additionally estimate a variant of equation (1) in which we interact the "treated" and "other" dummies with dummies indicating whether the company is financially constrained:

$$
\begin{aligned}
y_{ijlt} = \; & \alpha_i + \alpha_t + \alpha_l \times \alpha_t + \beta_1 \times \text{ treated}_{ijt} \times \text{ FC}_{jt} + \beta_2 \times \text{ treated}_{ijt} \times \text{ non-FC}_{jt} \\
& + \beta_3 \times \text{ other}_{ijt} \times \text{ FC}_{jt} + \beta_4 \times \text{ other}_{ijt} \times \text{ non-FC}_{jt} + \boldsymbol{\gamma}'\mathbf{X}_{ijlt} + \varepsilon_{ijlt}, \qquad (2)
\end{aligned}
$$

where FC is a dummy variable that equals one if a plant belongs to a company that is financially constrained.[12] Non-FC is defined analogously.

B. Measuring Financing Constraints

We use two popular measures of financing constraints: the Kaplan-Zingales (KZ) index (Kaplan and Zingales, 1997) and the Whited-Wu (WW) index (Whited and Wu, 2006). The Appendix describes how both measures are constructed.

Several papers have questioned the external validity of the KZ-index. A common critique is that the sample used to construct the KZ-index consists of manufacturing firms from the 1970s and 1980s. Accordingly, the loadings used to construct the KZ-index might be specific both to that period and to the manufacturing sector. This criticism is summarized in Whited and Wu (2006, p. 533):

> "One difficulty with this approach is parameter stability both across firms and over time. Kaplan and Zingales demonstrate convincingly that the firms they classify as constrained do indeed have the characteristics one would associate with external finance constraints. For example, they have high debt to capital ratios, and they appear to invest at a low rate, despite good investment opportunities. However, using the index coefficients on a much larger sample of

[12] To allow for different time trends between financially constrained and unconstrained firms, we could interact the year fixed effects with FC and non-FC dummies. Doing so would not affect our results.

> firms in a different time period leaves open the question of whether this index is truly capturing financial constraints."

We believe this shortcoming of the KZ-index, while potentially a problem in other contexts, is not a serious problem in our context. First, our sample consists only of manufacturing firms. Second, while our sample period goes beyond the 1970s and 1980s, we always use pre-treatment years to classify firms as financially constrained. These pre-treatment years are largely from the 1970s and 1980s, which overlaps well with the time period used by Kaplan and Zingales. Nevertheless, for robustness purposes, we estimate all regressions using both the KZ-index and the WW-index. As it turns out, all results are very similar regardless of which index we use.

To classify firms as financially constrained, we sort in each year all firms into two groups based on whether a firm's measure of financing constraints lies above or below the median in that year. If it lies above the median, the FC dummy is set equal to one. Otherwise, the non-FC dummy is set equal to one. While this implies that firms can move across groups over time, we are only interested in a firm's status at the time of the treatment. Accordingly, in order to determine whether a plant belongs to a firm that is financially constrained, we use the value of the firm's FC dummy *in the year prior to the treatment*. Using pre-treatment values mitigates concerns that our classification might be affected by the treatment itself.

Empirical studies using Compustat data typically classify about 30% to 40% of firms as financially constrained. Thus, our choice of a median cutoff may appear high. However, our sample is not representative of the Compustat universe. It includes only "pure" manufacturing firms, which are on average smaller than the typical Compustat firm—e.g., large conglomerates with operations outside of manufacturing are excluded from our sample—and thus more likely to be financially constrained. Indeed, if we applied our cutoffs (for the KZ- and WW-index) to the Compustat universe, we would obtain that 36.2% (KZ-index) and 31.8% (WW-index), respectively, of all firms are financially constrained. Such cutoffs are very much in line with the extant literature.[13]

[13] If we exclude utilities and financials, these cutoffs become 34.1% (KZ-index) and 36.4% (WW-index),

C. Empirical Methodology

The identification strategy follows Giroud (2012). To illustrate, suppose a company headquartered in Boston has plants located in Memphis, Chicago, and New York. In 1985, no direct flight was offered between Boston Logan International Airport and Memphis International Airport. The fastest way to connect both airports was an indirect flight operated by Delta Airlines with a stopover in Atlanta. In 1986, Northwest Airlines opened a new hub in Memphis. As part of this expansion, Northwest started operating direct flights between Boston and Memphis as of October 1986. The introduction of this new airline route reduced the travel time between Boston and Memphis and is coded as a "treatment" of the Memphis plant in 1986.[14] Accordingly, in 1986, the "treated" dummy switches from 0 to 1 for the Memphis plant, while the "other" dummy switches from 0 to 1 for the Chicago and New York plants.

The control group includes all plants that have not (yet) been treated or have not (yet) been "other" plants. This implies that, due to the staggered introduction of new airline routes, a plant remains initially in the control group until it becomes either a "treated" or "other" plant (which, for some plants, may be never).

Airlines' decisions to introduce new routes may depend on several factors, including economic and strategic considerations as well as lobbying. As long as these factors are orthogonal to plant-level investment and employment, this is not a concern. However, if there are (omitted) factors that are driving both the introduction of new airline routes and plant-level investment or employment, then any observed relationship between the two could be spurious.

One important source of endogeneity are (omitted) local shocks at the plant level. To continue with the above example, suppose the Memphis area experiences an economic boom. As a consequence, the company headquartered in Boston may find it more attractive to increase investment at the Memphis plant, while airlines may find it more attractive

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respectively.

[14] There was no reduction in travel time between Boston and either Chicago or New York in 1986. Indeed, there have always been direct flights between these locations since the beginning of our sample period.

to introduce new flights to Memphis, possibly due to lobbying by companies with plants in Memphis. Fortunately, since a treatment is uniquely defined by *two* locations—the plant's and headquarters' home airports—we are able to control for such shocks by including a full set of MSA $\times$ year fixed effects.[15]

All of these (endogeneity) concerns apply first and foremost to the treated plant. While it is conceivable that a local shock in the Memphis area might trigger both an increase in investment at the Memphis plant and the introduction of a new airline route between Boston and Memphis, it is less likely that a local shock in either the Chicago or New York area would trigger the introduction of a new airline route between Boston and Memphis.[16] Nevertheless, the inclusion of MSA-year fixed effects also accounts for this possibility.

Arguably, the introduction of a new airline route between Boston and Memphis—aside from making investment at the Memphis plant more attractive—should have no *direct* effect on the company's other (i.e., Chicago and New York) plants. To be clear, whether or not it has a direct effect does not affect the internal validity of our results: As long as the new airline route between Boston and Memphis is *exogenous* with respect to investment at the Chicago and New York plants, the coefficient on the "other" dummy will be identified.[17] However, it might affect the interpretation of our results. For instance, suppose the new airline route between Boston and Memphis had a direct negative effect on investment opportunities at the Chicago and New York plants. In that case, we could no longer say with confidence that a decline in investment at these plants is due to headquarters' reallocating scarce resources, for the same decline would have happened also

[15] To estimate the three-way fixed effect model with year, plant, and MSA-year fixed effects, we employ the estimation method proposed by Guimarães and Portugal (2010). (See also the discussion in Gormley and Matsa, 2012, especially Section 4.3.2.) In a previous version of this paper, we used time-varying MSA-year controls—defined as the mean of the dependent variable in the plant's MSA in a given year, excluding the plant itself—in lieu of MSA-year fixed effects. The results were virtually identical.

[16] Indeed, as we will see, other plants of the same firm may *suffer* from the introduction of a new airline route between headquarters and the treated plant. Thus, if anything, other plants might have an incentive to lobby *against* the introduction of the new airline route.

[17] To investigate the *causal* effect of the introduction of new airline routes, Giroud (2012) performs a number of additional tests. For instance, he shows that his results are robust if only new airline routes are considered that are the outcome of a merger between two airlines or the opening of a new hub, and if only indirect flights are considered where either the last leg of the flight (involving the plant's home base airport) or the first leg of the flight (involving headquarters' home base airport) remains *unchanged*. Our results are robust to performing any of these additional tests.

if the company was not financially constrained, simply because investment opportunities at these plants have suffered.

In this regard, looking at financially *unconstrained* firms provides us with a useful falsification (or placebo) test. As we will see, the introduction of a new airline route between headquarters and the treated plant has *no* effect on other plants if the firm is financially unconstrained. Arguably, if the new airline route had a direct negative effect on investment opportunities at other plants, then we should also observe a decline in investment at these plants if the firm is financially unconstrained.

D. Firm-Level Regressions

To examine the effect on the firm as a whole, we estimate the following firm-level analogue of equation (1):

$$y_{jt} = \alpha_j + \alpha_t + \beta_1 \times \text{ treatment}_{jt} + \boldsymbol{\gamma}'\mathbf{X}_{jt} + \varepsilon_{jt}, \tag{3}$$

where j indexes firms, t indexes years, α_j and α_t are firm and year fixed effects, y is the dependent variable, "treatment" is a dummy variable that equals one if a plant of firm j has been treated by year t, and $\mathbf{X}$ is a vector of control variables.

The main dependent variables are again investment and employment. Both variables are the same as in our plant-level regressions, except that they are aggregated at the firm level. For instance, firm-level investment is the ratio of total capital expenditures to total capital stock, where total capital expenditures (total capital stock) is the sum of capital expenditures (capital stock) across all of the firm's plants. Other dependent variables are the firm's return on capital (ROC), operating margin (OM), and total factor productivity (TFP). ROC is the ratio of total profits—i.e., the sum of shipments minus labor and material costs across all of the firm's plants—to total capital stock. OM is defined analogously, except that the denominator is total shipments.

To compute firm-level TFP, we follow Schoar (2002) and use the capital-weighted average of the individual plant-level TFPs. Plant-level TFP is the difference between actual and predicted output, where predicted output is the amount of output a plant is expected to produce for a given level of inputs. To compute predicted output, we follow common practice and use a log-linear Cobb-Douglas production function (e.g., Lichtenberg, 1992;

Schoar, 2002; Bertrand and Mullainathan, 2003; Syverson, 2004; Foster, Haltiwanger, and Syverson, 2008). Specifically, TFP of plant i in year t is the estimated residual from the regression:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \varepsilon_{it}, \tag{4}$$

where y is the logarithm of output and k, l, and m are the logarithms of capital, labor, and material inputs, respectively.[18] To allow for different factor intensities across industries and over time, we estimate equation (4) separately for each 3-digit SIC industry and year.[19] Thus, TFP measures the relative productivity of a plant *within* its industry.

The control variables are firm size and age. Firm size is the logarithm of total shipments—except in the ROC, OM, and TFP regressions, where it is the logarithm of capital stock—while firm age is the logarithm of one plus the number of years the firm has been in the LBD. To mitigate the effect of outliers, we winsorize all dependent variables at the 2.5th and 97.5th percentiles of their empirical distributions. As in our plant-level regressions, we cluster standard errors at the firm level.

To examine whether the treatment effect is different for financially constrained and unconstrained firms, we additionally estimate a variant of equation (3) in which the "treatment" dummy is interacted with dummies indicating whether the firm is financially constrained:

$$y_{jt} = \alpha_j + \alpha_t + \beta_1 \times \text{ treatment}_{jt} \times \text{ FC}_{jt} + \beta_2 \times \text{ treatment}_{jt} \times \text{ non-FC}_{jt} + \boldsymbol{\gamma}'\mathbf{X}_{jt} + \varepsilon_{jt}, \tag{5}$$

where FC and non-FC have been defined previously.

E. Measuring Travel Time Reductions

[18]While equation (4) is commonly estimated by OLS (see Syverson (2011) for a survey), research in structural industrial organization has proposed alternative methods to account for the endogeneity of input choices. Two prominent methods are those of Olley and Pakes (1996) and Levinsohn and Petrin (2003). We obtain similar results throughout if we compute TFP using these methods.

[19]SIC codes were the basis for all Census Bureau publications until 1996. In 1997, the Census Bureau switched to the North American Industry Classification System (NAICS). SIC codes were not discontinued until the 2002 Census, however. For the period from 2002 to 2005, SIC codes are obtained as follows. For plants "born" before 2002, we use the latest available SIC code. For plants born between 2002 and 2005, we convert NAICS codes into SIC codes using the concordance table of the Census Bureau.

A treatment is the introduction of a new airline route that reduces the travel time between headquarters and a plant relative to the previously optimal (i.e., fastest) way of traveling. There are four distinct possibilities: (i) a new indirect flight using a different route replaces a previously optimal indirect flight ("indirect to indirect"); (ii) a new direct flight replaces a previously optimal indirect flight, as in the Boston-Memphis example ("indirect to direct"); (iii) a new direct flight using a different route—i.e., either a different origination or destination airport—replaces a previously optimal direct flight ("direct to direct"); (iv) a new direct or indirect flight replaces car travel as the previously optimal means of transportation ("road to flight").

To compute the fastest way of traveling between headquarters and a given plant, we follow Giroud (2012) and determine the route and means of transportation (e.g., car, plane) that minimizes the total travel time (in minutes) between the plant's 5-digit ZIP code and that of headquarters (both from the LBD).[20] We first compute the driving time by car (in minutes) between the two ZIP codes using MS Mappoint. This travel time serves as a benchmark and is compared to the travel time by air based on the fastest airline route. Whenever traveling by car is faster, air transportation is ruled out by optimality, and the relevant travel time is the driving time by car.

To determine the fastest airline route between two ZIP codes, we use the itinerary information from the T-100 and ER-586 data. The fastest airline route minimizes the total travel time between headquarters and the plant. The total travel time consists of three components: 1) the travel time by car between headquarters and the origin airport, 2) the duration of the flight, including the time spent at airports and, for indirect flights, the layover time, and 3) the travel time by car between the destination airport and the plant. The travel time by car to and from the origin and destination airport, respectively, is obtained from MS Mappoint. Flight duration per segment is obtained from the T-100 and ER-586 data, which include the ramp-to-ramp time of all flights performed between any two airports in the U.S. The only unobservables are the time spent at airports and the layover time. We assume that one hour is spent at the origin and destination airports

[20]Precisely, we use the latitude and longitude corresponding to the centroid of the area spanned by the respective ZIP code.

combined and that each layover takes one hour. None of our results depend on these assumptions. In fact, we obtain virtually identical results using different assumptions.[21]

2.3 Summary Statistics

Table 1 presents summary statistics for all plants ("All Plants") and separately for plants that are treated during the sample period ("Eventually Treated Plants"), plants that become "other" plants during the sample period ("Eventually "Other" Plants"), and all remaining plants ("Remaining Plants"). For each plant characteristic, we report the mean and standard deviation (in parentheses). We cannot report median or other quantile values due to the Census Bureau's disclosure policy. All dollar values are expressed in 1997 dollars (in thousands).

As is shown, the three different categories of plants are very similar. For example, eventually treated plants have on average 379 employees compared to 432 employees at eventually "other" plants and 376 employees at all remaining plants. The only difference worth noting is that the remaining plants have slightly lower shipments and capital stock than the other two categories. This is not a concern, however. Due to the staggered introduction of new airline routes, plants in the "eventually treated" and "eventually other" categories are initially in the control group—together with the "remaining" plants—until they become either "treated" or "other" plants. Given the large number of plants in these two categories, this ensures that the control group is indeed *very* similar to the group of "treated" and "other" plants, respectively. In fact, one implication of the staggered introduction of new airline routes is that we can estimate all our regressions using only "eventually treated" and "eventually other" plants (see Bertrand and Mullainathan (2003) for a similar exercise).

We should note that the plants in our sample are larger than those in Giroud (2012). For example, the average plant in our sample has 410 employees versus 213 employees in Giroud's sample. This is not surprising, given that our sample includes only publicly

[21] The average layover time based on a random sample of 100 flights is approximately one hour. The time spent at the origin and destination airports is completely immaterial for our results as it cancels out when comparing "old" (i.e., previously optimal) and "new" flights.

traded companies that are covered in Compustat. Such companies are on average larger, and own larger plants, than private firms. On the other hand, our plants are slightly smaller than those in Bertrand and Mullainathan (2003), who also use a matched Census-Compustat sample, and who report an average of 436 employees per plant. This difference arises because our sample includes only "pure" manufacturing firms, while their sample also includes large conglomerates with substantial operations outside of manufacturing.

3 Results

Section 3.1 contains our basic plant-level regressions. Section 3.2 examines which "other" plants are primarily affected by the resource reallocation. Section 3.3 shows the aggregate (or net) effect on investment and employment at the firm level. To address whether the resource reallocation is overall beneficial, it also examines the aggregate effect on productivity at the firm level.

3.1 Plant-Level Regressions

Table 2 shows the effect of the introduction of new airline routes on the treated plant and on other plants of the same firm. In columns [1] to [3], the dependent variable is plant-level investment, while in columns [4] to [6], the dependent variable is plant-level employment. As column [1] shows, investment at the treated plant increases by 0.01 percentage points on average. Given that the average ratio of investment to capital stock at the plant level is 0.1, this implies an increase in investment at the treated plant of 1%. As for the firm's other plants, they experience a small but insignificant decline in investment on average. As we will see below, however, this effect becomes stronger if we focus on financially constrained firms and, in particular, on specific subsets of "other" plants.

Columns [2] and [3] display the effect separately for financially constrained and unconstrained firms. Several results are worth noting. First, in both cases, investment at the treated plant increases, albeit the effect is stronger for financially unconstrained firms: The coefficient on treated × FC is 0.008, while the coefficient on treated × non-FC is either 0.012 (KZ-index) or 0.011 (WW-index). The difference is significant at the 5% level. Second, the effect on investment at other plants of financially unconstrained firms is literally zero. Third, the effect on other plants of financially constrained firms is negative and—at least when the KZ-index is used—marginally significant.

The results in Table 2 suggest that financially constrained firms—but not financially unconstrained firms—exhibit negative spillovers across their plants. Indeed, the increase in investment at the treated plant is of the same order of magnitude as the decline at the other plants: At the treated plant, investment increases by $186,000, while it declines by $179,000 at all other plants together. This implies that, for financially constrained firms, the aggregate (or net) change in investment at the firm level should be roughly zero. We will confirm below that this is indeed true.

While our main focus is on financially constrained firms, looking at financially unconstrained firms provides us with a useful falsification (or placebo) test. Specifically, that the effect on other plants of financially unconstrained firms is literally zero suggests that the introduction of a new airline route between headquarters and the treated plant has *no direct effect* on other plants within the same firm. As we argued in Section 2.2.C, this matters for the interpretation of our results: If the new airline route had a direct effect on other plants, we could no longer say with confidence whether a decline in investment at those plants is due to headquarters' reallocating scarce resources or simply because the plants' investment opportunities have suffered.

Columns [4] to [6] display a similar pattern with respect to plant-level employment. In particular, while there are no spillovers at financially unconstrained firms, there are significant—at least when the KZ-index is used—spillovers at financially unconstrained firms. Indeed, the increase in employment at the treated plant is of the same order of magnitude as the decline at the other plants: At the treated plant, employment increases by five employees, while it declines by six employees at all other plants together.

That the patterns for investment and employment are so similar suggests that capital and labor are complements in the firm's production function. In untabulated regressions, we examine this hypothesis more directly by using the capital-to-labor ratio (logarithm of the ratio of capital stock to the number of employees) as the dependent variable. We find that this ratio remains unchanged throughout: at the treated plant, at the firm's other plants, and at the overall firm level. Hence, firms appear to respond to the treatment by adjusting capital and labor in a proportionate fashion.

Table 3 examines the dynamics of the treatment effect. Given that annual records in the CMF and ASM are measured in calendar years, the last month of each plant-year observation is December. Since the T-100 and ER-586 segment data are recorded at monthly frequency, this implies that we know precisely in which month a new airline route is introduced. Hence, we are able to reconstruct how many months before or after the introduction of a new airline route a plant-year observation is recorded. By exploiting this detailed knowledge of the dates at which new airline routes are introduced, we can introduce dummy variables indicating the time interval between a plant-year observation and the treatment. For instance, year(-1) indicates the plant-year observation in the year before the treatment, year(0) indicates the plant-year observation in the year of the treatment, and so on. Accordingly, treated × FC × year(-1) measures the effect on the treated plant for financially constrained firms in the year before the treatment, treated × FC × year(0) measures the same effect in the year of the treatment, and so on. Due to space constraints, Table 3 only reports the dynamics of the treatment effect for financially constrained firms.

Three results are worth noting. First, there are no existing pre-trends in the data. Both with regard to investment and employment, the treatment effect becomes significant only with a lag of about one year after the treatment. Second, the increase in investment and employment at the treated plant occurs around the same time as the decline at other plants. Indeed, it is reassuring that the timing between the treated plant and the other plants coincides so well, providing further evidence that headquarters channels scarce resources away from the other plants and toward the treated plant. Third, at least for financially constrained firms, the effect appears to fade away after a few years. Incidentally, the same is not true for financially unconstrained firms (untabulated results). For these firms, the increase in investment at the treated plant is permanent, albeit it becomes slightly weaker over time.

While our results suggest that headquarters takes away scarce resources from other plants, the *average* spillover effect shown in Table 2 is rather weak and (at best) marginally significant. There are several reasons for this. First, the amount of resources needed to "feed" the treated plant—and thus the amount that must be taken away from other plants—is fairly modest. Second, this amount is divided among many other plants, implying that the *average* amount that is taken away from any individual plant is relatively small. One immediate implication of this is that the spillover effect should become stronger if we focus on firms that have relatively few other plants. To see whether this is true, we interact other $\times$ FC and other $\times$ non-FC with dummy variables indicating whether the number of "other" plants lies below or above the median, respectively, across all treated firms in the year prior to the treatment. Indeed, as is shown in **Table 4**, the coefficient on other $\times$ FC becomes twice as large if we focus on firms with relatively few other plants. For example, the coefficient on other $\times$ FC $\times$ (# other plants $<$ median) is -0.004, while the coefficient on other $\times$ FC—i.e., the coefficient measuring the *average* spillover effect—was previously only -0.002 (see column [2] of Table 2). Moreover, the coefficient is now always significant at the 5% level, while it was previously either marginally significant or insignificant.[22]

Moreover, the average spillover effect is likely to be noisy, as headquarters does not uniformly "tax" all of the firm's other plants in the same way. While some plants may experience a large drop in their resources, others may experience none. To address this issue, we examine next which other plants are primarily affected by the resource reallocation. As we will show, if we focus on those plants, the spillover effect becomes again much stronger.

3.2 Which Other Plants Are Primarily Affected?

To examine which other plants are primarily affected by the resource reallocation, we interact other $\times$ FC with individual plant characteristics. These include plant productiv-

[22] We obtain a similar pattern if we sort firms into three equal groups based on the number of "other" plants: The coefficient on other $\times$ FC is monotonic across terciles and largest for firms that have relatively few other plants.

ity, whether the plant operates in a main or peripheral industry of the firm, whether it operates in the same or in a different industry as the treated plant, whether it has been newly acquired during the sample period, and whether it is "close" to headquarters in terms of geographical proximity or travel time. All plant characteristics are measured in the year prior to the treatment.[23]

Although our main focus is on financially constrained firms, we also interact other × non-FC with the same plant characteristics. Doing so provides us with a useful placebo test, as we would not expect to observe any significant effect on other plants of financially unconstrained firms. Indeed, in all of the regressions below, the coefficient on other × non-FC is always close to zero and insignificant, regardless of the specific plant characteristic. For brevity, we do not report the coefficients on treated × FC and treated × non-FC. These coefficients are virtually identical to before, whether or not they are interacted with plant characteristics. The remaining specification is the same as in Table 2, meaning it includes control variables, plant fixed effects, year fixed effects, and MSA × year fixed effects. **Table 5** reports pairwise correlations among the various plant characteristics. For any given pair of plant characteristics, we compute for all treated firms the within-firm correlation in the year prior to the treatment using all "other" plants and report the average among all financially constrained firms. As is shown, regardless of whether we use the KZ-index (Panel A) or WW-index (Panel B), all correlations are insignificant. The only exception is when two plant characteristics proxy for the same thing—e.g., TFP and ROC are both measures of plant productivity—in which case the pairwise correlation is, and should be, significant.

A. Plant Productivity

If headquarters wants to maximize overall efficiency, it should take away resources from those plants that are least productive. To see whether this is true, we interact other ×

[23] Eisfeldt and Rampini (2006) find that the capital reallocation *between* firms is procyclical. To see whether a similar result also holds *within* firms, we interact treated × FC and other × FC with business cycle dummies. (Precisely, we use the years before and after recession troughs, as identified by the NBER, to capture recession periods). Although we find no significant differences in the reallocation patterns across business cycles, we should note that our analysis captures only reallocations following *specific* events, namely, the introduction of new airline routes. Hence, a firm's *normal* capital reallocation may well exhibit a cyclical (or countercyclical) pattern.

FC with dummy variables indicating whether plant productivity lies below or above the median among all of the firm's "other" plants in the year prior to the treatment. Thus, productivity is measured relative to other plants *within* a firm, not across firms. We use two measures of plant productivity: total factor productivity (TFP) and the plant's return on capital (ROC).

As **Table 6** shows, financially constrained firms are indeed more likely to withdraw resources from their least productive plants. This is true regardless of how we measure plant productivity or financing constraints and regardless of whether we consider plant-level investment (Panel A) or plant-level employment (Panel B). Importantly, the coefficient on other $\times$ FC $\times$ low is always significant at the 5% level and is about twice as large as the corresponding coefficient on other $\times$ FC reported in Table 2. Thus, when we focus on the least productive plants within a firm, we obtain robust and significant spillover effects. Finally, the coefficient on other $\times$ FC $\times$ high is always small and insignificant and is always significantly different from that on other $\times$ FC $\times$ low.

B. Peripheral versus Main Industries

The second plant attribute that we consider proxies for how important a plant is for the firm as a whole. Specifically, we interact other $\times$ FC with dummy variables indicating whether a plant operates in a main or peripheral industry of the firm. Peripheral plants are those operating in (3- or 4-digit SIC) industries that account for less than 25% of the firm's total value of shipments in the year prior to the treatment (see Maksimovic and Phillips, 2002).

Table 7 presents the results. A quick look at the table shows that the results are qualitatively similar to those in Table 6. And yet, whether or not a plant operates in a main or peripheral industry is uncorrelated with its relative productivity (see the correlation matrix in Table 5). Specifically, the results show that financially constrained firms are indeed more likely to withdraw resources from peripheral plants. This is true regardless of how we measure financing constraints, whether we use 3- or 4-digit SIC industries to classify peripheral plants, and whether we consider plant-level investment (Panel A) or plant-level employment (Panel B). Importantly, the coefficient on other $\times$

FC $\times$ peripheral is (almost) always significant at the 5% level and is about twice as large as the corresponding coefficient on other $\times$ FC reported in Table 2. Finally, the coefficient on other $\times$ FC $\times$ main is always small and insignificant and is always significantly different from that on other $\times$ FC $\times$ peripheral.

C. Same versus Different Industries

The third plant attribute that we consider is whether a plant operates in the same or in a different industry as the treated plant. There are various reasons for why headquarters might want to withdraw more resources from plants that operate in the same industry as the treated plant. For example, doing so might minimize the impact on the firm's diversification strategy. Another reason is that—assuming divisions are organized by industry—adding and subtracting resources within the same industry might minimize wasteful inter-divisional rent-seeking.

While there may be good (theoretical) reasons for why headquarters might want to withdraw more resources from plants that operate in the same industry as the treated plant, we find no empirical support for such reasons. As is shown in **Table 8**, the coefficients on other $\times$ FC $\times$ same and other $\times$ FC $\times$ different are always close to each other and, consequently, also close to the coefficient on other $\times$ FC reported in Table 2.

D. Acquired versus Own Plants

The fourth plant attribute that we consider is whether a plant has been newly acquired during the sample period. There are again various reasons for why headquarters might want to withdraw more resources from newly acquired plants. For instance, newly acquired plants may have less lobbying power, or headquarters may know less about them than it does about plants that have been with the firm for a long time. However, we find no empirical support for such reasons. As **Table 9** shows, the coefficients on other $\times$ FC $\times$ acquired and other $\times$ FC $\times$ own are always close to each other and, consequently, also close to the coefficient on other $\times$ FC reported in Table 2.

E. Proximity to Headquarters

The final plant attribute that we consider is how "close" a plant is to headquarters. We use two measures of proximity: travel time and geographical distance, where the latter is computed using the great-circle distance formula

$$r \times \text{arcos}\ \left(\sin\lambda_P \sin\lambda_{HQ} + \cos\lambda_P \cos\lambda_{HQ} \cos[\phi_P - \phi_{HQ}]\right),$$

where λ_P (λ_{HQ}) and ϕ_P (ϕ_{HQ}) are the latitude and longitude, respectively, corresponding to the centroid of the area spanned by the ZIP code of the plant (headquarters), and r is the approximate radius of the earth (3,959 miles).

As **Table 10** shows, financially constrained firms are indeed more likely to withdraw resources from more distant plants. This is true regardless of how we measure proximity to headquarters or financing constraints and regardless of whether we consider plant-level investment (Panel A) or plant-level employment (Panel B). Importantly, the coefficient on other $\times$ FC $\times$ high is (almost) always significant at the 5% level and is about twice as large as the corresponding coefficient on other $\times$ FC reported in Table 2. Finally, the coefficient on other $\times$ FC $\times$ low is always small and insignificant and is always significantly different from that on other $\times$ FC $\times$ high.

3.3 Firm-Level Regressions

Table 11 presents the aggregate (or net) effect on investment and employment at the firm level. As column [1] shows, aggregate investment increases by 0.002 percentage points on average. Given that the average ratio of investment to capital stock at the firm level is 0.1, this implies an increase in firms' aggregate investment of 0.2%. Columns [2] and [3] display the aggregate effect separately for financially constrained and unconstrained firms. Regardless of which measure of financing constraints we use, we obtain the same picture: For financially constrained firms, aggregate investment remains unchanged, which is consistent with our previous result showing that the increase in investment at the treated plant is offset by a decrease at other plants of the same magnitude. In contrast, for financially unconstrained firms, the change in aggregate investment is positive. Given that financially unconstrained firms exhibit no (negative) spillovers among their plants, this is indeed what one would expect.

Columns [4] to [6] display a similar pattern with respect to employment at the firm level: While aggregate employment increases by 0.4% on average, firm-level employment at financially constrained firms remains unchanged, which is consistent with our previous result showing that the increase in employment at the treated plant is offset by a decrease at other plants of the same magnitude.

A key premise of the efficient internal capital markets paradigm is that the resource reallocation is beneficial: While resources may be taken away from projects that are positive NPV at the margin, they are channeled toward other projects whose investment prospects are *even* better. To explore this hypothesis, we consider the aggregate effect on productivity at the firm level. Doing so also helps us distinguish the efficient internal capital markets hypothesis from alternative stories, e.g., the resource reallocation might be the outcome of lobbying by managers of the treated plant, who suddenly find it easier to lobby given that their travel time to headquarters is reduced. While such lobbying efforts can explain why the treated plant gains at the expense of other plants, they are unlikely to yield an increase in firm-wide productivity.

Table 12 shows the results. In columns [1] to [3], the dependent variable is aggregate total factor productivity (TFP). In columns [4] to [6], the dependent variable is the firm's return on capital (ROC). Finally, in columns [7] to [9], the dependent variable is the firm's operating margin (OM). Regardless of which productivity measure we use, and regardless of how we measure financing constraints, we find that, for financially constrained firms, firm-wide productivity increases. Thus, it seems as though the channeling of resources away from the other plants and toward the treated plant is beneficial for the firm as a whole. For financially unconstrained firms, the firm-wide productivity increase is even higher, though this is not surprising given that these firms are not forced to take resources away from plants that are positive NPV at the margin.[24]

[24] Giroud (2012) illustrates how, in the context of the treated plant, this productivity increase translates into actual dollar profits. He also discusses whether there was "money left on the table," in the sense that it might have paid for headquarters to travel more often already prior to the treatment, use a private jet, or hire "delegated monitors." See Giroud (2012), especially Section III.C, for details. Note that the profit increase at the treated plant *overstates* the profit increase at the firm level, for two reasons. First, certain costs associated with the treatment, such as overhead costs and travel expenses, are assigned to

4 Conclusion

This paper documents how a plant-specific shock to investment opportunities at one plant of a firm ("treated plant") spills over to other plants of the same firm—but only if the firm is financially constrained: While investment and employment both increase at the treated plant, they both decline at other plants of the same firm. Moreover, the increase in investment and employment at the treated plant is of the same order of magnitude as the decline at other plants, implying that the aggregate (or net) effect at the firm level is zero. To determine whether the resource reallocation is beneficial, we examine its effect on aggregate productivity at the firm level. We find that—even if firms are financially constrained—firm-wide productivity increases, suggesting that the channeling of resources away from the other plants and toward the treated plant is beneficial for the firm as a whole.

We also explore which other plants are primarily affected by the resource reallocation. We find that financially constrained firms are more likely to withdraw resources from plants that are relatively less productive, are not part of the firm's core industries, and are located far away from headquarters. On the other hand, whether a plant operates in the same industry as the treated plant, or whether it has been newly acquired, plays no significant role for the resource reallocation.

Finally, our results have potential implications for internal labor markets. Unless workers are transferred across plants—which is less likely if the treated and the other plants are located far away from one another—our results suggest that the treated plant hires new workers while some of the other plants are forced to lay off workers. Hence, some workers are laid off not because their plant is doing poorly, but because some other plant within the same firm is doing relatively better. While this is speculative, this layoff risk due to headquarters engaging in "winner-picking" could be an explanation for Schoar's (2002) finding that conglomerates pay higher wages on average.

headquarters, not to the treated plant. Second, at least for financially constrained firms, the positive effect at the treated plant is partly offset by a negative effect at the firm's other plants.

5 Appendix: Measuring Financing Constraints

We use two popular measures to compute firms' financing constraints: the Kaplan-Zingales (KZ) index (Kaplan and Zingales, 1997) and the Whited-Wu (WW) index (Whited and Wu, 2006).

The KZ-index loads negatively on cash flow, cash holdings, and dividends, and positively on leverage and Tobin's Q. To compute the KZ-index, we follow Lamont, Polk, and Saa-Requejo (2001, pp. 551-552), who use the original coefficient estimates of Kaplan and Zingales. Precisely, the KZ-index is computed as:

$$\begin{aligned}\text{KZ-index} &= -1.001909 \times \text{cash flow/capital} + 0.2826389 \times \text{Tobin's Q} \\ &\quad +3.139193 \times \text{debt/total capital} - 39.3678 \times \text{dividend/capital} \\ &\quad -1.314759 \times \text{cash/capital},\end{aligned}$$

where cash flow/capital is income before extraordinary items (Compustat item #18) plus depreciation and amortization (item #14) divided by property, plant, and equipment (item #8), Tobin's Q is total assets (item #6) plus the December market value of equity from CRSP minus the book value of common equity (item #60) minus balance sheet deferred taxes (item #74) divided by total assets, debt/total capital is long-term debt (item #9) plus debt in current liabilities (item #34) divided by long-term debt plus debt in current liabilities plus stockholder's equity (item #216), dividend/capital is dividends on common stocks (item #21) plus dividends on preferred stocks (item #19) divided by property, plant, and equipment, and cash/capital is cash and short-term investments (item #1) divided by property, plant, and equipment. Property, plant, and equipment is lagged by one fiscal year. All variables are obtained from the annual files of Compustat and CRSP.

The WW-index represents the shadow value of scarce funds and loads negatively on cash flow, dividends, sales growth, and total assets, and positively on long-term debt and sales growth in the firm's industry. Following Whited and Wu (p. 543), we compute the

WW-index as:

$$\begin{aligned}\text{WW-index} &= -0.091 \times \text{cash flow/assets} - 0.062 \times \text{positive dividend} \\ &\quad +0.021 \times \text{long-term debt/assets} - 0.044 \times \log(\text{assets}) \\ &\quad +0.102 \times \text{industry sales growth} \ - 0.035 \times \text{sales growth},\end{aligned}$$

where cash flow/assets is income before extraordinary items (Compustat quarterly item #8) plus depreciation and amortization (item #5) divided by total assets (item #44), positive dividend is a dummy variable that equals one if cash dividend (item #89) is positive, long-term debt/assets is long-term debt (item #51) divided by total assets, log(assets) is the natural logarithm of total assets, sales growth is the growth in firm sales (item #2), and industry sales growth is sales growth in the firm's 3-digit SIC industry. Total assets is deflated by the replacement cost of total assets, which is computed as in Whited (1992). All variables are obtained from the quarterly file of Compustat. In our regressions, we annualize the WW-index by taking the average of the four quarterly WW-indices.

6 References

Alchian, Armen, 1969, Corporate Management and Property Rights, in: H. Manne (ed.), Economic Policy and the Regulation of Corporate Securities. Washington, DC: American Enterprise Institute.

Bertrand, Marianne, and Sendhil Mullainathan, 2003, Enjoying the Quiet Life? Corporate Governance and Managerial Preferences, Journal of Political Economy 111, 2003, 1043-1075.

Bolton, Patrick, and David Scharfstein, 1998, Corporate Finance, the Theory of the Firm, and Organizations, Journal of Economic Perspectives 12, 95-114.

Brusco, Sandro, and Fausto Panunzi, 2005, Reallocation of Corporate Resources and Managerial Incentives in Internal Capital Markets, European Economic Review 49, 659-681.

Eisfeldt, Andrea, and Adriano Rampini, 2006, Capital Reallocation and Liquidity, Journal of Monetary Economics 53, 369-399.

Foster, Lucia, John Haltiwanger, and Chad Syverson, 2008, Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability? American Economic Review 98, 394-425.

Giroud, Xavier, 2012, Proximity and Investment: Evidence from Plant-Level Data, Quarterly Journal of Economics, forthcoming.

Gormley, Todd, and David Matsa, 2012, Common Errors: How to (and Not to) Control for Unobserved Heterogeneity, mimeo, University of Pennsylvania.

Grossman, Sanford, and Oliver Hart, 1986, The Costs and Benefits of Ownership: A Theory of Vertical and Lateral Integration, Journal of Political Economy 94, 691-719.

Guimarães, Paulo, and Pedro Portugal, 2010, A Simple Feasible Procedure to Fit Models with High-Dimensional Fixed Effects, Stata Journal 10, 628-649.

Hart, Oliver, and John Moore, 1990, Property Rights and the Nature of the Firm, Journal of Political Economy 98, 1119-1158.

Holmström, Bengt, 1999, The Firm as a Subeconomy, Journal of Law, Economics, and Organization 15, 74-102.

Jarmin, Ron, and Javier Miranda, 2003, The Longitudinal Business Database, CES Working Paper.

Kaplan, Steven, and Luigi Zingales, 1997, Do Financing Constraints Explain Why Investment Is Correlated with Cash Flow? Quarterly Journal of Economics 112, 169-215.

Kroc, Ray, 1992, Grinding it Out: The Making of McDonald's. New York: St. Martin's Paperbacks.

Lamont, Owen, 1997, Cash Flow and Investment: Evidence from Internal Capital Markets, Journal of Finance 52, 83-109.

Lamont, Owen, Christopher Polk, and Jesus Saa-Requejo, 2001, Financial Constraints and Stock Returns, Review of Financial Studies 14, 529-554.

Levinsohn, James, and Amil Petrin, 2003, Estimating Production Functions Using Inputs to Control for Unobservables, Review of Economic Studies 70, 317-341.

Lichtenberg, Frank, 1992, Corporate Takeovers and Productivity. Cambridge, MA: MIT Press.

Maksimovic, Vojislav, and Gordon Phillips, 2002, Do Conglomerate Firms Allocate Resources Inefficiently Across Industries? Theory and Evidence, Journal of Finance 57, 721-767.

Maksimovic, Vojislav, and Gordon Phillips, 2008, The Industry Life Cycle, Acquisitions and Investment: Does Firm Organization Matter? Journal of Finance 63, 673-707.

Milgrom, Paul, 1988, Employment Contracts, Influence Activities and Efficient Organization Design, Journal of Political Economy 96, 42-60.

Milgrom, Paul, and John Roberts, 1988, An Economic Approach to Influence Activities and Organizational Responses, American Journal of Sociology 94 (Supplement), S154-S179.

Olley, Steven, and Ariel Pakes, 1996, The Dynamics of Productivity in the Telecommunications Equipment Industry, Econometrica 64, 1263-1297.

Rajan, Raghuram, Henri Servaes, and Luigi Zingales, 2000, The Cost of Diversity: The Diversification Discount and Inefficient Investment, Journal of Finance 55, 35-80.

Scharfstein, David, and Jeremy Stein, 2000, The Dark Side of Internal Capital Markets: Divisional Rent-Seeking and Inefficient Investment, Journal of Finance 55, 2537-2564.

Schoar, Antoinette, 2002, Effects of Corporate Diversification on Productivity, Journal of Finance 57, 2379-2403.

Shin, Hyun-Han, and René Stulz, 1998, Are Internal Capital Markets Efficient? Quarterly Journal of Economics 113, 531-552.

Stein, Jeremy, 1997, Internal Capital Markets and the Competition for Corporate Resources, Journal of Finance 52, 111-133.

Syverson, Chad, 2004, Market Structure and Productivity: A Concrete Example, Journal of Political Economy 112, 1181-1222.

Syverson, Chad, 2011, What Determines Productivity? Journal of Economic Literature 49, 326-365.

Tate, Geoffrey, and Liu Yang, 2011, The Bright Side of Corporate Diversification: Evidence from Internal Labor Markets, mimeo, UCLA.

Whited, Toni, 1992, Debt, Liquidity Constraints, and Corporate Investment: Evidence from Panel Data, Journal of Finance 47, 1425-1460.

Whited, Toni, and Guojun Wu, 2006, Financial Constraints Risk, Review of Financial Studies 19, 531-559.

Williamson, Oliver, 1975, Market and Hierarchies: Analysis and Antitrust Implications. New York: Free Press.

Table 1
Summary Statistics

"All Plants" refers to all plants in the sample. "Eventually Treated Plants" refers to plants that are treated during the sample period, i.e., plants whose travel time to headquarters is reduced through the introduction of a new airline route. "Eventually Other Plants" refers to plants that become "other" plants during the sample period. "Remaining Plants" refers to all remaining plants. Employees is the number of employees of the plant. Shipments, capital stock, and investment are expressed in 1997 dollars (in 1,000s) using 4-digit SIC deflators from the NBER-CES Manufacturing Industry Database. Capital stock is constructed using the perpetual inventory method. All figures are sample means. Standard deviations are in parentheses. The sample period is from 1977 to 2005.

	All Plants	Eventually Treated Plants	Eventually "Other" Plants	Remaining Plants
Employees	410	379	432	376
	(929)	(756)	(968)	(975)
Shipments	97,255	95,403	103,929	79,235
	(360,818)	(304,582)	(360,623)	(411,983)
Capital Stock	42,078	41,666	45,756	31,501
	(141,084)	(139,036)	(147,219)	(122,738)
Investment	3,848	3,646	3,969	3,701
	(53,589)	(15,735)	(21,316)	(113,504)
Investment / Capital Stock	0.10	0.10	0.10	0.11
	(0.14)	(0.13)	(0.14)	(0.16)
Number of Observations	291,358	61,007	172,667	57,684

Table 2
Main Plant-Level Regressions

Investment is the ratio of capital expenditures to capital stock at the plant level. Employment is the natural logarithm of the number of employees of the plant. "Treated" is a dummy variable that equals one if a new airline route that reduces the travel time between the plant and its headquarters has been introduced. "Other" is a dummy variable that equals one if a plant belongs to the same firm as a treated plant and the treated dummy is equal to one. FC (Non-FC) is a dummy variable that equals one if the plant belongs to a firm whose measure of financing constraints lies above (below) the median across all firms in the year prior to the treatment. In columns [2] and [5], financing constraints are measured using the KZ-index of Kaplan and Zingales (1997). In columns [3] and [6], financing constraints are measured using the WW-index of Whited and Wu (2006). Control variables include size and age. Size is the natural logarithm of the plant's shipments. Age is the natural logarithm of one plus the number of years since the plant has been in the LBD. Standard errors are clustered at the firm level. The sample period is from 1977 to 2005. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Investment			Employment		
		KZ-Index	WW-Index		KZ-Index	WW-Index
	[1]	[2]	[3]	[4]	[5]	[6]
Treated	0.010***			0.025***		
	(0.001)			(0.004)		
Other	-0.001			-0.002		
	(0.001)			(0.003)		
Treated × FC		0.008***	0.008***		0.019***	0.019**
		(0.002)	(0.003)		(0.006)	(0.008)
Treated × Non-FC		0.012***	0.011***		0.028***	0.026***
		(0.002)	(0.001)		(0.005)	(0.004)
Other × FC		-0.002*	-0.003		-0.006*	-0.007
		(0.001)	(0.002)		(0.004)	(0.006)
Other × Non-FC		0.000	-0.000		0.001	-0.000
		(0.001)	(0.001)		(0.004)	(0.003)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Plant Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	291,358	291,358	291,358	291,358	291,358	291,358
R-squared	0.32	0.32	0.32	0.92	0.92	0.92

Table 3
Dynamics of the Treatment Effect

This table presents variants of the plant-level regressions in columns [2]-[3] and [5]-[6], respectively, of Table 2, where Other × FC and Other × Non-FC are interacted with dummy variables indicating whether the plant-year observation is measured one year before the treatment (-1), in the year of the treatment (0), one, two, and three years after the treatment (1, 2, and 3, respectively), and four or more years after the treatment (4+). All other variables are described in Table 2. Standard errors are clustered at the firm level. The sample period is from 1977 to 2005. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Investment		Employment	
	KZ-Index	WW-Index	KZ-Index	WW-Index
	[1]	[2]	[3]	[4]
Treated × FC × Year(-1)	-0.003	0.002	-0.003	-0.002
	(0.004)	(0.005)	(0.011)	(0.017)
Treated × FC × Year(0)	0.005	0.004	0.004	0.003
	(0.003)	(0.006)	(0.010)	(0.014)
Treated × FC × Year(1)	0.014***	0.014***	0.031***	0.041***
	(0.003)	(0.004)	(0.010)	(0.014)
Treated × FC × Year(2)	0.009**	0.010*	0.029***	0.030***
	(0.003)	(0.005)	(0.008)	(0.012)
Treated × FC × Year(3)	0.008*	0.008*	0.019**	0.022*
	(0.004)	(0.005)	(0.010)	(0.014)
Treated × FC × Year(4+)	0.006	0.006	0.013	0.013
	(0.004)	(0.005)	(0.011)	(0.015)
Other × FC × Year(-1)	0.001	0.002	0.001	0.001
	(0.002)	(0.003)	(0.006)	(0.008)
Other × FC × Year(0)	-0.001	-0.002	-0.002	-0.002
	(0.002)	(0.004)	(0.007)	(0.009)
Other × FC × Year(1)	-0.005**	-0.006**	-0.017***	-0.020**
	(0.002)	(0.003)	(0.006)	(0.010)
Other × FC × Year(2)	-0.004*	-0.005	-0.011*	-0.014
	(0.002)	(0.003)	(0.006)	(0.009)
Other × FC × Year(3)	-0.002	-0.002	-0.006	-0.010
	(0.002)	(0.003)	(0.006)	(0.010)
Other × FC × Year(4+)	-0.001	-0.002	-0.003	-0.002
	(0.002)	(0.003)	(0.006)	(0.009)
Treated × Non-FC	0.012***	0.012***	0.027***	0.026***
	(0.002)	(0.001)	(0.005)	(0.004)
Other × Non-FC	0.001	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.004)	(0.003)
Control Variables	Yes	Yes	Yes	Yes
Plant Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
MSA × Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	291,358	291,358	291,358	291,358
R-squared	0.32	0.32	0.92	0.92

Table 4
Firms with Few and Many "Other" Plants

This table presents variants of the plant-level regressions in columns [2] and [3] and columns [5] and [6], respectively, of Table 2, where Other × FC and Other × Non-FC are interacted with dummy variables indicating whether the number of "other" plants lies below or above the median, respectively, across all treated firms in the years prior to the treatment. All other variables are described in Table 2. Standard errors are clustered at the firm level. The sample period is from 1977 to 2005. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Investment		Employment	
	KZ-Index	WW-Index	KZ-Index	WW-Index
	[1]	[2]	[3]	[4]
Treated × FC	0.008***	0.008***	0.019***	0.019**
	(0.002)	(0.003)	(0.006)	(0.008)
Treated × Non-FC	0.012***	0.011***	0.028***	0.026***
	(0.002)	(0.001)	(0.005)	(0.004)
Other × FC × (# Other Plants < Median)	-0.004**	-0.005**	-0.011**	-0.014**
	(0.002)	(0.003)	(0.006)	(0.007)
Other × FC × (# Other Plants ≥ Median)	-0.001	-0.002	-0.003	-0.002
	(0.002)	(0.004)	(0.006)	(0.010)
Other × Non-FC × (# Other Plants < Median)	0.000	-0.001	0.001	0.001
	(0.002)	(0.002)	(0.006)	(0.005)
Other × Non-FC × (# Other Plants ≥ Median)	0.001	0.000	-0.000	-0.001
	(0.002)	(0.001)	(0.004)	(0.004)
Control Variables	Yes	Yes	Yes	Yes
Plant Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
MSA × Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	291,358	291,358	291,358	291,358
R-squared	0.32	0.32	0.92	0.92

Table 5
Correlation Matrix

For each pair of plant characteristics, this table reports the average within-firm correlation among all "other" plants of financially constrained firms in the year prior to the treatment. In Panel (A), financing constraints are measured using the KZ-index of Kaplan and Zingales (1997). In Panel (B), financing constraints are measured using the WW-index of Whited and Wu (2006). Total factor productivity (TFP) is the residual from estimating a log-linear Cobb-Douglas production function by Ordinary Least Squares separately for each 3-digit SIC industry and year at the plant level. (See Section 2.2.D for more details.) Return on capital (ROC) is the value of shipments minus labor and material costs divided by capital stock. Peripheral plants operate in (3- or 4-digit SIC) industries that account for less than 25% of the firm's total value of shipments. Geographical distance is the great-circle distance between the plant's ZIP code and the ZIP code of headquarters. Travel time is the total travel time based on the fastest route and means of transportation (car or plane) between the plant's ZIP code and the ZIP code of headquarters. Same industry is a dummy variable that equals one if the plant operates in the same (3- or 4-digit SIC) industry as the treated plant. Acquired is a dummy that equals one if the plant was acquired by the firm during the sample period. *p*-values are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): KZ-Index

	TFP	ROC	Peripheral Plant (3-digit SIC)	Peripheral Plant (4-digit SIC)	Travel Time	Geographical Distance	Same Industry (3-digit SIC)	Same Industry (4-digit SIC)	Acquired Plant
TFP	1.000								
ROC	0.578***	1.000							
	(0.002)								
Peripheral Plant (3-digit SIC)	-0.052	-0.039	1.000						
	(0.824)	(0.874)							
Peripheral Plant (4-digit SIC)	-0.057	-0.037	0.822***	1.000					
	(0.823)	(0.887)	(0.000)						
Travel Time	-0.015	-0.033	0.073	0.093	1.000				
	(0.955)	(0.904)	(0.770)	(0.741)					
Geographical Distance	-0.010	-0.014	0.066	0.093	0.857***	1.000			
	(0.972)	(0.959)	(0.795)	(0.745)	(0.000)				
Same Industry (3-digit SIC)	0.004	0.033	-0.191	-0.146	-0.067	-0.079	1.000		
	(0.989)	(0.900)	(0.625)	(0.703)	(0.864)	(0.840)			
Same Industry (4-digit SIC)	-0.003	0.029	-0.175	-0.180	-0.032	-0.053	0.870***	1.000	
	(0.992)	(0.910)	(0.618)	(0.633)	(0.934)	(0.890)	(0.000)		
Acquired Plant	0.011	0.054	0.003	0.009	-0.032	-0.031	0.179	0.146	1.000
	(0.966)	(0.826)	(0.992)	(0.976)	(0.938)	(0.939)	(0.634)	(0.700)	

Panel (B): WW-Index

	TFP	ROC	Peripheral Plant (3-digit SIC)	Peripheral Plant (4-digit SIC)	Travel Time	Geographical Distance	Same Industry (3-digit SIC)	Same Industry (4-digit SIC)	Acquired Plant
TFP	1.000								
ROC	0.550**	1.000							
	(0.012)								
Peripheral Plant (3-digit SIC)	-0.060	-0.047	1.000						
	(0.810)	(0.863)							
Peripheral Plant (4-digit SIC)	-0.060	-0.050	0.850***	1.000					
	(0.821)	(0.853)	(0.000)						
Travel Time	-0.008	-0.022	0.101	0.112	1.000				
	(0.978)	(0.941)	(0.729)	(0.720)					
Geographical Distance	-0.001	-0.006	0.092	0.102	0.863***	1.000			
	(0.998)	(0.983)	(0.755)	(0.742)	(0.000)				
Same Industry (3-digit SIC)	0.001	0.032	-0.176	-0.129	-0.052	-0.052	1.000		
	(0.997)	(0.913)	(0.636)	(0.723)	(0.901)	(0.904)			
Same Industry (4-digit SIC)	0.003	0.029	-0.138	-0.145	-0.017	-0.027	0.879***	1.000	
	(0.992)	(0.921)	(0.677)	(0.683)	(0.967)	(0.949)	(0.000)		
Acquired Plant	-0.015	0.039	0.030	0.038	0.027	0.039	0.154	0.110	1.000
	(0.956)	(0.877)	(0.924)	(0.902)	(0.950)	(0.930)	(0.705)	(0.784)	

Table 6
Plant Productivity

This table presents variants of the plant-level regressions in columns [2] and [3] and columns [5] and [6], respectively, of Table 2, where Other × FC and Other × Non-FC are interacted with dummy variables (“Low” and “High”) indicating whether plant productivity lies below or above the median productivity across all of the firm’s “other” plants in the year prior to the treatment. Productivity is measured using TFP in columns [1] and [2] and ROC in columns [3] and [4]. The dependent variable is investment in Panel (A) and employment in Panel (B). TFP and ROC are described Table 5. All other variables are described in Table 2. For brevity, the coefficients on Treated × FC and Treated × Non-FC are omitted from the table. Standard errors are clustered at the firm level. The sample period is from 1977 to 2005. Standard errors are in parentheses (except for the *F*-statistics, where *p*-values are in parentheses). *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Investment

	TFP		ROC	
	KZ-Index	WW-Index	KZ-Index	WW-Index
	[1]	[2]	[3]	[4]
Other × FC × Low	-0.005**	-0.006**	-0.005**	-0.006**
	(0.002)	(0.003)	(0.002)	(0.003)
Other × FC × High	0.001	0.001	0.001	0.001
	(0.002)	(0.003)	(0.002)	(0.003)
Other × Non-FC × Low	0.000	-0.001	0.000	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)
Other × Non-FC × High	0.001	0.000	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Other × FC × Low versus Other × FC × High				
F-statistic	3.92**	3.00*	3.89**	2.91*
	(0.048)	(0.083)	(0.049)	(0.088)

Panel (B): Employment

	TFP		ROC	
	KZ-Index	WW-Index	KZ-Index	WW-Index
	[1]	[2]	[3]	[4]
Other × FC × Low	-0.011**	-0.015**	-0.011**	-0.015**
	(0.006)	(0.008)	(0.006)	(0.008)
Other × FC × High	-0.002	0.004	-0.002	0.004
	(0.006)	(0.009)	(0.006)	(0.009)
Other × Non-FC × Low	0.000	-0.001	0.000	-0.002
	(0.005)	(0.004)	(0.005)	(0.004)
Other × Non-FC × High	0.003	-0.000	0.003	0.000
	(0.005)	(0.004)	(0.005)	(0.004)
Other × FC × Low versus Other × FC × High				
F-statistic	3.31*	3.07*	3.50*	2.70*
	(0.069)	(0.080)	(0.061)	(0.100)

Table 7
Peripheral versus Main Industries

This table presents variants of the plant-level regressions in columns [2] and [3] and columns [5] and [6], respectively, of Table 2, where Other × FC and Other × Non-FC are interacted with dummy variables ("Peripheral" and "Main") indicating whether a plant operates in a peripheral or main industry of the firm in the year prior to the treatment. Industries are classified using 3-digit SIC codes in columns [1] and [2] and 4-digit SIC codes in columns [3] and [4]. The dependent variable is investment in Panel (A) and employment in Panel (B). Peripheral industries are described in Table 5. All other variables are described in Table 2. For brevity, the coefficients on Treated × FC and Treated × Non-FC are omitted from the table. Standard errors are clustered at the firm level. The sample period is from 1977 to 2005. Standard errors are in parentheses (except for the *F*-statistics, where *p*-values are in parentheses). *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Investment

	3-digit SIC		4-digit SIC	
	KZ-Index	WW-Index	KZ-Index	WW-Index
	[1]	[2]	[3]	[4]
Other × FC × Main	0.000	-0.001	0.000	-0.001
	(0.002)	(0.003)	(0.002)	(0.003)
Other × FC × Peripheral	-0.005**	-0.006**	-0.005**	-0.006**
	(0.002)	(0.003)	(0.002)	(0.003)
Other × Non-FC × Main	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Other × Non-FC × Peripheral	-0.000	-0.001	-0.000	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)
Other × FC × Main versus Other × FC × Peripheral				
F-statistic	3.48*	3.03*	2.96*	3.00*
	(0.062)	(0.082)	(0.085)	(0.083)

Panel (B): Employment

	3-digit SIC		4-digit SIC	
	KZ-Index	WW-Index	KZ-Index	WW-Index
	[1]	[2]	[3]	[4]
Other × FC × Main	0.002	0.003	0.003	0.002
	(0.006)	(0.008)	(0.006)	(0.008)
Other × FC × Peripheral	-0.011**	-0.017**	-0.012**	-0.016*
	(0.006)	(0.009)	(0.006)	(0.009)
Other × Non-FC × Main	0.003	0.002	0.003	0.003
	(0.006)	(0.005)	(0.006)	(0.005)
Other × Non-FC × Peripheral	0.000	-0.002	0.000	-0.003
	(0.005)	(0.004)	(0.005)	(0.004)
Other × FC × Main versus Other × FC × Peripheral				
F-statistic	3.33*	3.20*	3.93**	3.67*
	(0.068)	(0.073)	(0.047)	(0.055)

Table 8
Same versus Different Industries

This table presents variants of the plant-level regressions in columns [2] and [3] and columns [5] and [6], respectively, of Table 2, where Other × FC and Other × Non-FC are interacted with dummy variables ("Same" and "Different") indicating whether a plant operates in the same industry as the treated plant in the year prior to the treatment. Industries are classified using 3-digit SIC codes in columns [1] and [2] and 4-digit SIC codes in columns [3] and [4]. The dependent variable is investment in Panel (A) and employment in Panel (B). All other variables are described in Table 2. For brevity, the coefficients on Treated × FC and Treated × Non-FC are omitted from the table. Standard errors are clustered at the firm level. The sample period is from 1977 to 2005. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Investment

	3-digit SIC		4-digit SIC	
	KZ-Index	WW-Index	KZ-Index	WW-Index
	[1]	[2]	[3]	[4]
Other × FC × Same	-0.003	-0.003	-0.003	-0.003
	(0.003)	(0.004)	(0.003)	(0.004)
Other × FC × Different	-0.002	-0.003	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Other × Non-FC × Same	0.001	-0.001	0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Other × Non-FC × Different	0.000	-0.000	0.000	-0.000
	(0.002)	(0.001)	(0.002)	(0.001)

Panel (B): Employment

	3-digit SIC		4-digit SIC	
	KZ-Index	WW-Index	KZ-Index	WW-Index
	[1]	[2]	[3]	[4]
Other × FC × Same	-0.004	-0.008	-0.004	-0.008
	(0.008)	(0.012)	(0.008)	(0.012)
Other × FC × Different	-0.006	-0.006	-0.006	-0.006
	(0.005)	(0.007)	(0.005)	(0.007)
Other × Non-FC × Same	0.002	0.001	0.002	0.001
	(0.006)	(0.005)	(0.006)	(0.005)
Other × Non-FC × Different	0.001	-0.002	0.000	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)

Table 9
Acquired versus Own Plants

This table presents variants of the plant-level regressions in columns [2] and [3] and columns [5] and [6], respectively, of Table 2, where Other × FC and Other × Non-FC are interacted with dummy variables ("Acquired" and "Own") indicating whether a plant was acquired by the firm during the sample period. The dependent variable is investment in Panel (A) and employment in Panel (B). All other variables are described in Table 2. For brevity, the coefficients on Treated × FC and Treated × Non-FC are omitted from the table. Standard errors are clustered at the firm level. The sample period is from 1977 to 2005. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Investment

	Acquired versus Own Plant	
	KZ-Index	WW-Index
	[1]	[2]
Other × FC × Own	-0.003	-0.003
	(0.002)	(0.002)
Other × FC × Acquired	-0.002	-0.004
	(0.002)	(0.005)
Other × Non-FC × Own	0.000	-0.000
	(0.001)	(0.001)
Other × Non-FC × Acquired	0.000	-0.001
	(0.003)	(0.002)

Panel (B): Employment

	Acquired versus Own Plant	
	KZ-Index	WW-Index
	[1]	[2]
Other × FC × Own	-0.007	-0.008
	(0.005)	(0.007)
Other × FC × Acquired	-0.006	-0.006
	(0.007)	(0.015)
Other × Non-FC × Own	0.000	-0.001
	(0.004)	(0.004)
Other × Non-FC × Acquired	0.001	0.000
	(0.008)	(0.005)

Table 10
Proximity to Headquarters

This table presents variants of the plant-level regressions in columns [2] and [3] and columns [5] and [6], respectively, of Table 2, where Other × FC and Other × Non-FC are interacted with dummy variables ("Low" and "High") indicating whether the travel time and geographical distance, respectively, lies below or above the median across all of the firm's "other" plants in the year prior to the treatment. The dependent variable is investment in Panel (A) and employment in Panel (B). Travel time and geographical distance are described in Table 5. All other variables are described in Table 2. For brevity, the coefficients on Treated × FC and Treated × Non-FC are omitted from the table. Standard errors are clustered at the firm level. The sample period is from 1977 to 2005. Standard errors are in parentheses (except for the *F*-statistics, where *p*-values are in parentheses). *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Investment

	Travel Time		Geographical Distance	
	KZ-Index	WW-Index	KZ-Index	WW-Index
	[1]	[2]	[3]	[4]
Other × FC × Low	0.001	0.001	0.000	0.001
	(0.002)	(0.003)	(0.002)	(0.003)
Other × FC × High	-0.005**	-0.006**	-0.004**	-0.006**
	(0.002)	(0.003)	(0.002)	(0.003)
Other × Non-FC × Low	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Other × Non-FC × High	0.000	-0.001	0.000	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)
Other × FC × Low versus Other × FC × High				
F-statistic	3.61*	3.40*	2.80*	3.59*
	(0.057)	(0.065)	(0.094)	(0.058)

Panel (B): Employment

	Travel Time		Geographical Distance	
	KZ-Index	WW-Index	KZ-Index	WW-Index
	[1]	[2]	[3]	[4]
Other × FC × Low	0.000	0.004	0.002	0.004
	(0.006)	(0.009)	(0.006)	(0.009)
Other × FC × High	-0.011**	-0.015*	-0.012**	-0.015*
	(0.006)	(0.008)	(0.006)	(0.008)
Other × Non-FC × Low	0.002	0.001	0.001	0.001
	(0.005)	(0.004)	(0.005)	(0.004)
Other × Non-FC × High	0.001	-0.001	0.002	-0.001
	(0.005)	(0.004)	(0.005)	(0.004)
Other × FC × Low versus Other × FC × High				
F-statistic	3.31*	3.07*	3.08*	3.27*
	(0.069)	(0.080)	(0.079)	(0.071)

Table 11
Main Firm-Level Regressions

Investment is the ratio of total capital expenditures to total capital stock, where total capital expenditures (total capital stock) is the sum of capital expenditures (capital stock) across all of the firm's plants. Employment is the natural logarithm of the total number of employees across all of the firm's plants. "Treatment" is a dummy variable that equals one if a plant of the firm has been treated, i.e., if a new airline route has been introduced that reduces the travel time between headquarters and one of the firm's plants. FC (Non-FC) is a dummy variable that equals one if the firm's measure of financing constraints lies above (below) the median across all firms in the year prior to the treatment. In columns [2] and [5], financing constraints are measured using the KZ-index of Kaplan and Zingales (1997). In columns [3] and [6], financing constraints are measured using the WW-index of Whited and Wu (2006). Control variables include firm size and firm age. Firm size is the natural logarithm of total shipments across all of the firm's plants. Age is the natural logarithm of one plus the number of years the firm has been in the LBD. Standard errors are clustered at the firm level. The sample period is from 1977 to 2005. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Investment			Employment		
		KZ-Index	WW-Index		KZ-Index	WW-Index
	[1]	[2]	[3]	[4]	[5]	[6]
Treatment	0.002***			0.004**		
	(0.001)			(0.002)		
Treatment × FC		0.000	0.000		-0.000	0.001
		(0.001)	(0.001)		(0.002)	(0.003)
Treatment × Non-FC		0.004***	0.003***		0.009***	0.006***
		(0.001)	(0.001)		(0.002)	(0.002)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,695	33,695	33,695	33,695	33,695	33,695
R-squared	0.41	0.41	0.41	0.88	0.88	0.88

Table 12
Is the Resource Reallocation Beneficial?

This table presents variants of the firm-level regressions in Table 11 using different dependent variables. Firm-level total factor productivity (TFP) is the capital-weighted average of individual plant-level TFPs across all of the firm's plants, where plant-level TFP is defined in Table 5. Firm-level return on capital (ROC) is the ratio of total profits—i.e., the sum of shipments minus labor and material costs across all of the firm's plants—to total capital stock. Firm-level operating margin (OM) is defined analogously, except that the denominator is total shipments (i.e., the sum of shipments across all of the firm's plants). Control variables include firm size and firm age. Firm size is the natural logarithm of total capital stock across all of the firm's plants. Age is the natural logarithm of one plus the number of years the firm has been in the LBD. All other variables are described in Table 11. Standard errors are clustered at the firm level. The sample period is from 1977 to 2005. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	TFP			ROC			OM		
		KZ-Index	WW-Index		KZ-Index	WW-Index		KZ-Index	WW-Index
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Treatment	0.003***			0.004***			0.003***		
	(0.001)			(0.001)			(0.001)		
Treatment × FC		0.002**	0.002**		0.003**	0.003**		0.002**	0.002*
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Treatment × Non-FC		0.005***	0.004***		0.006***	0.005***		0.004***	0.004***
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,695	33,695	33,695	33,695	33,695	33,695	33,695	33,695	33,695
R-squared	0.51	0.51	0.51	0.61	0.61	0.61	0.65	0.65	0.65