Resource Redeployment as an Entry Advantage in Resource-Poor Settings

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Abstract

Scarcity of productive factors poses a challenge for firms entering underdeveloped regions. We examine resource redeployment as a strategy to overcome scarcity in factor markets by modeling when expanding firms will internally redeploy versus hire workers via external markets. Our model predicts that redeployment is most valuable when there are large differences in resource scarcity across factor markets and when output is highly sensitive to worker skill and complementarities between labor and other resources. The ability to overcome resource scarcity allows firms with redeployment capabilities to enter markets that other firms would not. Data on sugar mills in Brazil, where a sudden demand boom incentivized expansion, corroborate the predictions. Our research identifies new entry advantages from resource redeployment.

Keywords: resource redeployment, strategic factor markets, labor market thickness, human capital, market entry

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1 INTRODUCTION

Multi-unit and multi-business firms are the behemoths of modern economies; how they grow and create value is one of the central questions of strategy research (see Feldman, 2020 for review). A growing body of work focuses on advantages that such firms derive from the option to internally redeploy resources—such as human, technological, and physical capital—across their units over time (Folta, Helfat, & Karim, 2016; Helfat & Eisenhardt, 2004; Karim & Capron, 2016; Sakhartov & Folta, 2015). Redeployment allows firms to more easily expand in product markets with strong opportunities and exit or retrench from markets facing worse prospects (Anand, 2004; Anand & Singh, 1997; Chang & Matsumoto, 2022; Dickler & Folta, 2020; Giarratana & Santaló, 2020; Lieberman, Lee, & Folta, 2017; Miller & Yang, 2016; Wu, 2013). This strategic flexibility to redeploy resources is especially valuable when intra-firm resource movements are more efficient than using external markets (Folta, 2021; Helfat & Eisenhardt, 2004; Sohl & Folta, 2021).

Although research provides significant insight into how firms benefit from redeployment as they navigate changes in the relative performance of *product markets*, few studies have examined the benefits of redeployment in helping firms overcome frictions and imperfections in *factor markets* (Belenzon & Tsolmon, 2016; Berry & Kaul, 2021; Tate & Yang, 2015). Strategic factor markets—markets for the inputs that firms use to implement their strategies (Barney, 1986)—frequently exhibit resource scarcity, i.e., limited supply of a productive factor (Dierickx & Cool, 1989; Mahoney & Qian, 2013; Peteraf, 1993).[1] The degree of resource scarcity can differ both

[1] Consistent with the literature, we view scarcity as the inelastic supply of a valuable resource in a strategic factor market, which indicates that the resource supply is insufficient to satisfy (latent) demand (Barney, 1991; Peteraf, 1993). It can result from inherent characteristics of a resource and/or from market circumstances, and can encompass both temporary and permanent inelasticity (e.g., Chadwick, 2017).

across types of resources (e.g., human capital vs. financial capital) and across different local markets. For example, the market for software engineers exhibits greater scarcity in Montana than in Mountain View, California. Yet, little is known about how resource scarcity in factor markets affects firms' decisions to acquire resources versus redeploy them internally. Failing to consider redeployment as a tool for navigating differences in resource scarcity results in only a partial understanding of how firms create value from their resources, and when redeployment capabilities contribute to superior economic performance.

In this paper, we examine when firms use redeployment strategies to overcome scarcity in strategic factor markets for human capital. Building on the insight that "thickness"—the supply of workers with specialized skills—varies across local labor markets (Bleakley & Lin, 2012; Moretti, 2011), we present a model in which incumbent firms entering new markets can hire locally or redeploy workers from existing markets, which incurs a one-time redeployment cost and the opportunity cost of the foregone use of the worker in the origin (Levinthal & Wu, 2010). Key insights of the model are that differences in the extent of resource scarcity across factor markets present opportunities for firms to profitably redeploy resources. Further, redeployment is more valuable when output is more sensitive to heterogeneity in worker skill and when complementarities between labor and other factors of production create opportunities to assign employees to where they are best matched with complementary inputs. More broadly, our model indicates that firms possessing redeployment capabilities can enter markets that are *a priori* unattractive due to resource scarcity but are ex-post profitable due to redeployment's ability to substitute for local, externally acquired resources.

We test these predictions in the sugar processing industry in Brazil, which offers an ideal empirical context. The introduction of flex-fuel vehicles that can run on gasoline or ethanol in the early 2000s drastically increased the demand for sugarcane. As a result, firms expanded production into previously undeveloped regions. Using employer-employee matched data, we examine the market entry, external hiring, and internal redeployment decisions of the population of sugar mills from 2000 to 2014, a period in which land-area dedicated to sugarcane increased by more than 70 percent (Assunção, Pietracci, & Souza, 2016). We find direct evidence for the model's predictions that incumbent firms use redeployment to support market entry and show that this tendency is significantly stronger the thinner the labor markets in the new location and the thicker the labor markets of existing units. Furthermore, we show that redeployment endowed mills of incumbent firms with entry advantages—notably larger initial size and higher levels of human capital—relative to mills of *de novo* firms.

Our main contribution is demonstrating a new source of corporate advantage from firms' capability to tap into multiple factor markets and overcome resource scarcity through redeployment. While research explains how redeployment allows firms to transfer resources across product markets with different levels of profitability (Dickler & Folta, 2020; Giarratana & Santaló, 2020; Miller & Yang, 2016; Sakhartov & Folta, 2014; Wu, 2013), we show how redeployment also enables firms to allocate resources across geographic markets with different levels of resource munificence. As such, we identify differences in resource scarcity across factor markets as a new, underexplored source of inducements (Sakhartov & Folta, 2014, 2015) that spur resource redeployment. We add to a small set of empirical studies that explore redeployment benefits tied to conditions in factor markets. While Belenzon & Tsolmon (2016) and Tate & Yang (2015) highlight how internal labor markets help firms attenuate transaction costs—such as firing frictions—we shed light on the critical role of redeployment in overcoming resource scarcity.

Therefore, we expand our understanding of how firms create value from their resources and when redeployment capabilities contribute to superior economic performance.

We also contribute to research on redeployment and market entry (Belenzon, Bennett, & Patacconi, 2019; Lieberman et al., 2017; Santamaria, 2022). In Lieberman et al. (2017) and Belenzon et al. (2019), redeployment lowers sunk costs associated with entry by allowing firms to redeploy resources if a business fails. As a result, multi-unit and multi-business firms attempt more entries, but the average quality of these entries is lower. In contrast, we highlight the use of redeployment to overcome resource scarcity as a different mechanism that facilitates entry, one with distinct implications for the types of opportunities firms pursue. The capability to overcome resource scarcity predicts redeployment at the time of *entry* rather than exit and facilitates not only more entry but also predicts that the expected performance of the businesses conditional on entry is *higher*. Thus, we highlight higher productivity at entry, rather than lower sunk cost, as another mechanism through which resource redeployment facilitates firm entry.

Our work also relates to research on the superior economic performance of business groups (e.g., Khanna & Rivkin, 2001; Khanna & Palepu, 2000) and incumbent firms in emerging market settings (Chang & Wu, 2014; Kim, Hoskisson, & Lee, 2015). Like the business group literature, we highlight internal markets as a solution for imperfections in external markets. Relative to the business group literature, our focus is to incorporate opportunity cost and redeployment costs into the redeployment decision, which enables us to test specific predictions regarding *when* redeployment is likely and where redeployed resources come *from* and are redeployed *to* (Folta et al., 2016). We also highlight a new mechanism—better access to scarce factors of production—as an explanation for the observation that the entry threshold for new firms tends to be higher than that for incumbent firms, especially in less-developed markets (Fisman & Khanna, 2004).

Finally, this paper answers a call for research on firm growth (Agarwal & Helfat, 2009; Helfat, 2021) and how firms can take advantage of opportunities in resource-poor settings (Chakrabarti, Vidal, & Mitchell, 2011; Marquis & Raynard, 2015). Our study indicates that redeployment capabilities are a critical advantage for firms seeking to enter undeveloped markets.

2 THEORY AND HYPOTHESES

We model when firms expanding into new markets acquire resources in external factor markets versus redeploy them from existing units, and how redeployment affects performance relative to *de novo* firms that cannot redeploy. We predict that redeployment is most valuable and likely to occur: (a) when firms operate across factor markets with large differences in resource scarcity, (b) when output is highly sensitive to differences in resource quality, and (c) when complementarities between resources encourage firms to assign resources to their most productive use. The model indicates that redeployment enables firms to overcome resource scarcity, which might otherwise hamper productivity and limit market entry. While we focus on the redeployment of human capital—a resource with local external factor markets—the insights can be applied generally to resources that exhibit different degrees of mobility frictions in external versus internal markets.

2.1 A Model of Redeployment with Differences in Factor Market Scarcity

We consider the market entry and staffing problem for a firm over three periods in a context where production requires labor and land, with skilled labor differing in scarcity across locations. Resource scarcity in a local labor market is the opposite of “thickness,” which is the probability of finding workers with *industry-specific skills* (Moretti, 2011; Neal, 1995). Following Hausmann and Neffke (2019), we model scarcity using the probability a newly hired worker is high-skill. We first restrict our attention to a single initial market and describe the firm’s factor acquisition and production problem over two periods. In the third period, we introduce the firm's decision to expand into a second, "frontier" market and whether to hire locally or redeploy workers from the initial market. **Figure 1** illustrates the structure and timing of the model.

In the first period ($t = 1$), the firm decides whether to pay a one-time fixed cost, $F_I > 0$, to enter the initial market and access the local factor markets. If the firm enters, it acquires a parcel of land with known quality z_I and hires a single worker of unknown skill.[2] In the second period ($t = 2$), the firm produces. With probability $\lambda_I > 0$ the worker is high-skill and produces output according to $f_H(z)$. With probability $1 - \lambda_I$ the worker is low-skill and produces output according to $f_L(z)$. We make the following definitional assumptions about production:

Assumption 1. High-skill workers have an absolute advantage in production:

$$f_H(z) > f_L(z) \geq 0 \; \forall z$$

Assumption 2. Output is monotonically increasing in land quality:

$$f_i'(z) > 0 \quad \forall i \in \{L, H\}$$

The definition of "high-skill" is the ability to produce more output with the same level of input (Assumption 1), and the definition of "land quality" is that better land yields more output for a worker of given skill (Assumption 2).

We assume employment contracts must offer a fixed wage $w_I \geq 0$, and because skill is unobservable, all workers earn the same wage (Mas-Colell, Whinston, & Green, 1995).[3] Because

[2] We denote parameters in the initial market with the subscript I because we introduce a second market in Section 2.2 below. We use land and labor as inputs because our empirical setting is agricultural. Our arguments do not depend on z being land. We do rely, however, on the usual assumption that one input is non-scale free (Levinthal & Wu, 2010).

[3] We provide further details regarding our assumptions about wages in the online appendix, but otherwise treat wages as exogenous and constant throughout because wage differences do not motivate our hypotheses.

our focus is factor markets, we assume the product market is perfectly competitive and that the firm faces perfectly elastic demand for a final good with price $p_I > 0$. Finally, we assume fixed costs are low enough that the firm enters.[4] Expected profits (net of fixed costs) at $t = 2$ are:

$$\pi_I = p_I \underbrace{[\lambda_I f_H(z_I) + (1 - \lambda_I) f_L(z_I)]}_{\text{Expected output}} - \underbrace{(w_I + F_I)}_{\text{Costs}} \tag{1}$$

In the third and final period ($t = 3$), the firm chooses one of two actions in the initial market: (a) operate with the worker hired in the previous period, or (b) fire the existing worker and operate with a new hire. A consequence of Assumption (1) is that the firm learns the worker's type following production.[5] This knowledge informs the firm's choice in the third period. The firm will always retain a high-skill worker but will never retain a low-skill worker because the expected output of a new hire exceeds $f_L(z)\ \forall z, \lambda$ given $\lambda > 0$.[6]

2.2 A Second Market and the Redeployment Decision

Immediately before third-period production, a second business opportunity becomes available such that the firm can operate in one or both markets during the third and final period ($t = 3$). The new opportunity—which we call the "frontier"—is structured identically to the initial market but lasts for a single period that occurs in parallel with the final period in the initial market. Using subscript N to denote parameters in the new frontier, the firm pays a fixed cost $F_N > 0$ to enter and can hire a local worker who is high-skill with probability $\lambda_N > 0$. Production functions in the frontier and initial market are identical, but land quality is z_N rather than z_I. The price of output is

[4] We more formally present the conditions for market entry in Appendix B.

[5] Since land quality is known, a firm can attribute observation of $f_H(z_I)$ to having hired a high-skill worker and observation of $f_L(z_I)$ to having hired a low-skill worker.

[6] Whether a firm has a high-skill worker at this stage can be attributed to luck (Makadok & Barney, 2001).

p_N and the wage is w_N, which we assume is less than or equal to initial market wage ($w_N \leq w_I$).[7] Mirroring Equation (1), *de novo* entrants in the frontier market face the following profit function:

$$\pi_N = p_N \underbrace{[\lambda_N f_H(z_N) + (1 - \lambda_N) f_L(z_N)]}_{\text{Expected output in frontier}} - \underbrace{(w_N + F_N)}_{\text{Costs in frontier}} \tag{2}$$

Unlike *de novo* entrants, however, firms in the initial market can choose between hiring a worker in the frontier or redeploying the worker hired at $t = 1$ in the initial market for a fixed redeployment cost, $R \geq 0$. For simplicity, we assume that *de novo* firms in the frontier cannot hire from the initial market without paying F_I to establish a presence in that market, in which case they would not be *de novo* firms but instead resemble incumbents.[8]

A firm with a low-skill worker in the initial market will never redeploy because the expected value of firing and replacing a low-skill worker always exceeds the expected value of retaining or redeploying the worker.[9] Consequently, only firms with high-skill workers consider redeployment.

If the incumbent firm hires from the frontier, it resembles a *de novo* entrant and hires a high-skill worker with probability λ_N. If the firm redeploys its initial, high-skill worker, however, it is guaranteed high output in the frontier.[10] In this case, it replaces the initial worker with a new hire

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[7] Our empirical context has identical prices across markets ($p_I = p_N$), but we present the case with different prices for generality. The assumption $w_N \leq w_I$ clarifies the presentation because, when we consider redeployment, the firm must pay a redeployed worker $\max\{w_I, w_N\}$. Rather than repeatedly write this expression, we assume $w_N \leq w_I$. This is consistent with our empirical setting and the notion of the new market being an undeveloped frontier.

[8] Similarly, we assume that workers do not relocate themselves across markets, which is consistent with a large literature in urban economics (e.g., Autor, Dorn, & Hanson, 2013; Topalova, 2010). Among the most examined types of mobility frictions are idiosyncratic worker preferences over locations (e.g., Diamond, 2016), imperfect information about opportunities (e.g., Wilson, 2021), and migration costs (e.g., Monte, Redding, & Rossi-Hansberg, 2018). Choudhury (2020) reviews literature that suggests that such mobility frictions may be lower for intra-firm mobility.

[9] The maximum profit in the frontier from redeploying a low-skill worker equals the profit the from hiring a low-skill worker in the frontier. This is strictly less, however, than the expected profit of hiring from the frontier given $\lambda_N > 0$.

[10] Upon redeployment, the firm knows that the initial worker is highly skilled. This is consistent with the idea that firms have better information about their employees than about external hires. Though our model does not assume any

who is high-skill with probability λ_I. Furthermore, when the firm redeploys, the profit function in the frontier includes a fixed redeployment cost and reflects the fact that redeployed workers must be paid their (higher) wage from the initial market because otherwise they would not move. Third-period profits in the initial and frontier markets conditional on entry are summarized in Table 1.

As Table 1 shows, the firm weighs the benefits of redeployment in the frontier against the redeployment cost and opportunity cost of withdrawing the worker from the initial market. If at least one entry strategy is profitable, the firm will prefer redeployment to local hiring when:

$$\underbrace{p_N(1-\lambda_N)[f_H(z_N)-f_L(z_N)]}_{\text{Expected gain in frontier market}} - \underbrace{p_I(1-\lambda_I)[f_H(z_I)-f_L(z_I)]}_{\text{Opportunity cost in initial market}} > \underbrace{w_I - w_N + R}_{\text{Cost of redeployment}} \quad (3)$$

The left-side of the inequality in Equation (3) represents the net benefit of redeployment, and the right-side represents the total cost of redeployment. Factors affecting the benefit of redeployment include resource scarcity in the initial and frontier markets (λ_I and λ_N), resource heterogeneity, which is the high-skill workers' productivity advantage ($f_H(z) - f_L(z)$), the quality of complementary factors (z_I and z_N), and prices (p_I and p_N). Below, we analyze how resource scarcity, resource heterogeneity, and the quality of complementary inputs affect redeployment.[11]

2.2.1 The effects of resource scarcity

Differentiating the left-side of Equation (3) with respect to labor market thickness in the frontier (λ_N) and initial market (λ_I) gives:

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benefits of job matching or firm-specific skills, research shows that these factors affect the performance of redeployed workers in their new jobs. Bidwell (2011) maintains that redeployed workers initially perform better than external hires due to differences in firm-specific skills and match quality. Workers hired internally show higher levels of firm-specific skills, which are important for work performance; also, these workers and their firms have better information about each other, which helps identify job opportunities that suit workers' preferences and abilities.

[11] We analyze prices in the online appendix; other papers emphasize demand conditions (e.g., Anand & Singh, 1997; Dickler & Folta, 2020; Giarratana & Santaló, 2020; Wu, 2013), and our results are consistent with the literature.

$$\frac{\partial}{\partial \lambda_2} = -p_2[f_H(z_2) - f_L(z_2)] < 0 \text{ and } \frac{\partial}{\partial \lambda_1} = p_1[f_H(z_1) - f_L(z_1)] > 0 \quad (4)$$

Because high-skill workers are more productive than low-skill workers (Assumption 1), the derivative with respect to λ_N is negative and the derivative with respect to λ_I is positive. Thus, the net gain from redeployment is greater when high-skill workers are scarce in the frontier (λ_N is small) and abundant in the initial market (λ_I is high). Intuitively, "arbitraging" factor market differences is most valuable when the frontier is resource-poor and when the firm can easily replace a high-skill worker in the initial market. This result motivates the following hypotheses:

> **Hypothesis 1a.** *Conditional on entry in a market, firms are more likely to staff positions via redeployment than via external labor markets the lower the thickness of the local labor market* (λ_N).

> **Hypothesis 1b.** *Conditional on entry in a market, firms are more likely to staff positions via redeployment than via external labor markets the higher the thickness of the labor market(s) in which the firm already operates* (λ_I).

2.2.2 The effects of resource heterogeneity

To predict how the magnitude of high-skill workers' advantage $\left(f_H(z) - f_L(z)\right)$—the degree of worker heterogeneity—affects redeployment, we examine shifts in this advantage of the form:

$$h(z) = a + f_H(z) - f_L(z)$$

where a is a parameter for factors that affect the size of the productivity difference between skill levels. Substituting this into Equation (3) produces the following condition for redeployment:

$$p_N(1 - \lambda_N)h(z_N) - p_I(1 - \lambda_I)h(z_I) > w_I - w_N + R \quad (5)$$

Differentiating the left-side—the net benefit of redeployment—with respect to a (a change in high-skill workers' productivity advantage) gives:

$$\frac{\partial}{\partial a} = p_N(1 - \lambda_N) - p_I(1 - \lambda_I) \tag{6}$$

Intuitively, $p_N(1 - \lambda_N)$ is the expected additional value created by redeployment in the frontier, and $p_I(1 - \lambda_I)$ is the expected loss of withdrawing a high-skill worker from the initial market—i.e., the change in opportunity cost due to a change in a. If output prices are equal across markets ($p_I = p_N = p$) and human capital is scarcer in the frontier ($\lambda_N < \lambda_I$) (which matches our empirical setting; see Section 3), Equation (6) equals $p(\lambda_I - \lambda_N) > 0$, which indicates that redeployment is more beneficial as the difference between high- and low-skill workers increases.[12] For some jobs, marginal productivity with respect to skill is low, while for others, small differences in talent have large effects on outcomes (Sattinger, 1975; Teulings, 1995). Therefore, we predict:

> **Hypothesis 2.** *Conditional on market entry and labor market thickness in existing and new markets, firms are more likely to staff positions via redeployment than via external labor markets in occupations in which output is more sensitive to differences in worker skill.*

In addition to this main effect, Equations (4)–(6) show there is an interaction effect between labor market thickness and factors that affect the productivity advantage of high-skill workers. As $f_H(z) - f_L(z)$ increases, both derivatives in Equation (4) increase in magnitude. In other words, differences in labor market thickness have larger effects on the benefit of redeployment in settings where obtaining high-skill workers is more consequential for production. We hypothesize:

> **Hypothesis 3.** *The effect of labor market thickness on worker redeployment will be stronger in occupations in which output is more sensitive to differences in worker skill.*

[12] Relatedly, Bidwell & Keller (2014) suggest firms prefer internal over external hiring for jobs with greater performance variability.

2.2.3 The effects of complementarities

Equations (3) and (4) show how an input that is not subject to market failure and cannot be redeployed (land in our model) can nevertheless affect redeployment and moderate the effect of resource scarcity (such as the availability of high-skill workers). Differentiating Equation (3) with respect to land quality in each market gives:

$$\frac{\partial}{\partial z_N} = p_N(1-\lambda_N)g'(z_N) \quad \text{and} \quad \frac{\partial}{\partial z_I} = -p_I(1-\lambda_I)g'(z_I), \qquad (7)$$

$$\text{where } g(z) = f_H(z) - f_L(z)$$

And taking the derivative of Equation (4) with respect to land quality—a second derivative of Equation (3)—gives:

$$\frac{\partial}{\partial \lambda_N \partial z_N} = -p_N g'(z_N) \text{ and } \frac{\partial}{\partial \lambda_I \partial z_I} = p_I g'(z_I) \qquad (8)$$

The signs of the partial derivatives in Equations (7) and (8) depend on the sign of $g'(z)$. Thus, the effects of land quality on the benefit of redeployment and the role of land in moderating the effects of labor market thickness (the interaction effect of thickness and land quality) depend on whether the marginal productivity of skill increases or decreases with the quality of land—i.e., whether production is supermodular, submodular, or neither.

Figure 2 illustrates three scenarios when the frontier has lower quality land ($z_N < z_I$). If production is supermodular and $g'(z) > 0$ as in **Figure 2**(a), then the advantage of a high-skill worker is greater when they are assigned better inputs. In this case, the benefit of redeployment increases with land quality in the frontier ($\partial/\partial z_N > 0$) and the effect of labor market thickness on redeployment is more negative on better land ($\partial/\partial\lambda_N \partial z_N < 0$). If production is submodular as in **Figure 2**(b), then $g'(z) < 0$ and the high-skill worker is most valuable in the difficult frontier. In this case, better frontier land reduces the net benefit of redeployment and weakens the relationship between thickness and redeployment in Hypotheses 1a–b. Finally, if the advantage of a high skill worker is the same on bad and good land as in **Figure 2**(c), then the net benefit of redeployment is insensitive to land quality and the effect of thickness on redeployment will not vary with land quality because $g'(z) = 0 \; \forall z$ implies all derivatives in Equations (7)–(8) vanish.

The key intuition behind these patterns is that how much a firm values the high-skill worker depends on how that worker's skill interacts with other resources used in production. In practice, this depends on the exact nature of the production process, and any scenario depicted in **Figure 2** can hold.[13] More generally, these patterns illustrate how redeployment decisions can be viewed as an assignment problem in which value creation hinges on the firm's capability to form bundles of complementary resources (Lippman & Rumelt, 2003).

While this analysis makes novel predictions about complementarity and redeployment, and suggests examining heterogeneity in the effects of labor market thickness across markets with varying land quality, we lack strong priors about the supermodularity of the production function in our empirical setting (fuel ethanol manufacturing). We therefore treat analyses of land and its interaction with thickness as exploratory. We can, however, predict that if the benefit of worker skill varies with land quality, then the effects of land in the frontier and initial market on redeployment should have opposite signs:

Hypothesis 4. *The effect of the quality of the complementary resource in the initial market on redeployment will be opposite in sign from the effect of the quality of complementary resource in the new market, unless both effects are zero.*

[13] For example, Sattinger (1975) develops an assignment model in which high-skill workers have a comparative advantage in more difficult tasks, which is analogous to high-skill workers being most beneficial on bad land. Garicano & Rossi-Hansberg (2006) develop a model in which better managers supervise better subordinates, which resembles the case of high-skill workers being most valuable when given high-quality land.

2.3 Model Summary and Implications

To summarize, we develop a model in which redeployment emerges as an optimal strategy for firms operating in multiple markets with varying degrees of resource scarcity. We show how redeployment allows firms to overcome resource scarcity in factor markets, which extends and complements the emphasis in the redeployment literature on shifting resources in response to changes in the attractiveness of product markets (Sakhartov & Folta, 2015; Dickler & Folta, 2020; Santaló & Giarratana, 2020). Our perspective offers an alternative to other models of the entry advantage from redeployment (Lieberman et al., 2017; Belenzon et al., 2019; Santamaria, 2021). In these models, firms possess an option to exit businesses that turn out poorly by redeploying their resources to other ventures. This redeployment option induces firms to enter markets that are riskier in expectation because they can recover a portion of fixed costs if the business sours. Empirically, these extant models predict that firms predominantly (a) redeploy resources away from bad businesses, (b) realize the benefit of redeployment when exiting, and (c) enter businesses that perform worse on average than those pursued by *de novo* entrants.

In our model, firms exercise their option to redeploy resources *at the time of entry* and the redeployment decision itself affects the probability that a business succeeds. Thus, the benefit of redeployment is realized at the time of *entry* rather than exit by endowing firms with superior resources. Despite modeling the benefits of redeployment differently, a commonality between our model and others is that firms with strong redeployment capabilities pursue business opportunities that *de novo* entrants and firms with weak redeployment capabilities may not. We highlight how markets that look a priori economically unattractive can be ex-post profitable due to redeployment's ability to substitute for local, externally acquired resources. Therefore, we show how redeployment not only mitigates the "sunkness" of investments (Lieberman et al., 2017;

Belenzon et al., 2019; Santamaria, 2021) but also allows firms to overcome market imperfections that might otherwise hamper productivity and prevent entry.

3 THE SUGAR INDUSTRY IN BRAZIL

In this section, we provide additional background on our empirical setting, the sugar growing and processing industry in Brazil. Brazil is the largest producer and exporter of sugarcane in the world, contributing 26 percent of total world supply in 2000 and 39 percent in 2014.[14] In the 1970s, the Brazilian government began investing heavily in the sector as part of the National Alcohol Program (*Proálcol*) with the goal of counteracting large increases in oil prices by promoting the production of fuel ethanol from sugar (da Cunha, Ribeiro, & Guarenghi, 2019). Between 1975 and 1998, when the sector was deregulated, production of sugarcane in Brazil more than tripled (da Cunha et al., 2019). The favorable economics for sugar ethanol production in Brazil spurred R&D investments in flex-fuel vehicle technology, which allows automobiles to run on either gasoline or ethanol. Major breakthroughs in the industry occurred in the early 2000s, when car manufactures began to commercialize vehicles capable of running on any mix of ethanol and gasoline. Sales of flex-fuel vehicles increased dramatically following their introduction in 2003 (Figure 3a), reaching more than 80 percent of all new vehicle registrations in Brazil by 2007. The success of flex-fuel vehicles in Brazil increased demand for fuel ethanol, which led to an increase in demand for sugarcane (da Cunha et al., 2019). Between 2000 and 2014 (the last year of our sample), fuel ethanol production increased by 212 percent, sugarcane production increased by 142 percent, and the total land area dedicated to sugarcane production increased by 109 percent (Figure 3b).

[14] Source: UN Food and Agriculture Organization (FAO).

Several features of the expansion of sugarcane and fuel ethanol production in Brazil make it an ideal setting for testing our theory. First, the large increase in demand for sugarcane was exogenous to developments in the sugar industry itself and instead stemmed from developments in flex-fuel vehicle technology. Second, firms had little choice but to open new sugar mills in previously undeveloped regions (Adami et al., 2012). Transporting sugarcane is not economical because it loses sugar content very rapidly after being harvested and, therefore, mills must locate within a 50 km radius of where the cane is grown (Sant'Anna, Shanoyan, Bergtold, Caldas, & Granco, 2016). The difficulty of increasing yields or expanding growing areas around existing mills pushed firms to open new mills in regions that offered suitable land for sugarcane but where the industry was previously undeveloped. In the 2000–2014 period, 122 new sugar mills opened in Brazil, many in western "frontier" states (Figure 4). Third, the final product—ethanol fuel—is homogeneous and its price varies little across markets. These features allow us to better isolate how differences in factor market conditions—underexplored in the redeployment literature—rather than differences in the prices of final goods, affect redeployment decisions.

4 DATA AND MEASUREMENT

Our analysis combines employer-employee matched data covering the population of Brazilian formal firms and workers with data on local labor markets and agricultural conditions.

4.1 Employer-employee matched data

Our main data source is the *Relação Annual de Informações Sociais* (RAIS), an annual census of all employers and their employees in Brazil's formal economy. This census is mandatory and covers everyone employed by a formal establishment in Brazil, along with their occupation, wage, age, gender, education, month of hiring, month of departure, and other variables. RAIS provides a tax ID number for each establishment and the equivalent of a social security number for each worker.[15] Observations belonging to the same worker can be linked across census years and across establishments or firms. We use this feature of the data to measure worker redeployment as the hiring of a worker who held a position at another mill belonging to the same firm.

4.2 Sample: Sugar mills

We use the industry codes for sugar cultivation, processing, refining and ethanol production in RAIS to identify all sugar mills in operation between 1994 and 2014, their geographic locations, and all workers they ever employed.[16] We cross-check RAIS against multiple other data sources to verify our sample and identify their parent firms.[17] First, we match CNPJs in RAIS to CNPJs in the Ministry of Agriculture's registry of sugar plants (SAPCana).[18] Registration in SAPCana is mandatory for all industrial units, cooperatives, and trading companies producing sugar in Brazil. Second, we match mills in RAIS to the registry of ethanol production plants maintained by the National Petroleum Agency (ANP).[19] We identify 463 mills that operated in Brazil between 1994 and 2014 (the "sample").[20]

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[15] Each establishment is identified in RAIS with a unique 14-digit *Cadastro Nacional da Pessoa Jurídica* (CNPJ) tax ID number. The first eight digits of the CNPJ identify the firm.

[16] Industries are identified using the five-digit *Classificação Nacional de Atividades Econômicas* (CNAE). We use versions 1.0 and 2.0 of CNAE (CNAE 1.0 codes 01139, 15610, 15628, 23400; CNAE 2.0 codes 01130, 10716, 10724, 19314) to compile all firms that were ever involved in sugar production.

[17] A sugar/ethanol mill may contain multiple establishments and even multiple firms (e.g., a firm dedicated to sugar cultivation and another dedicated to sugar processing), and we identify all CNPJs linked to a particular mill using their 8-digit CNPJ and geographic location. By using the sugar/ethanol mill, instead of the establishment, as the unit of analysis, we ignore the redeployment of workers across establishments or firms within the same mill, which could occur for tax purposes and have no material change in the place of work.

[18] Source: https://sistemasweb4.agricultura.gov.br/sapcana/downloadBaseCompletaInstituicao.action. Last accessed on June 15, 2022.

[19] Source: https://cpl.anp.gov.br/anp-cpl-web/public/etanol/consulta-produtores/consulta.xhtml. Last accessed on June 15, 2022.

[20] Mills in the registries that did not match RAIS using the CNPJ were manually inspected and matched using the location (state and municipality) data provided in the registries.

The sugar mills in our sample may be independent ("standalone") mills or belong to business groups. To identify business groups, we use information from NovaCana,[21] a specialized news portal for the sugar sector that provides information on all mills in Brazil, including their location and group affiliation. We assemble the ownership history of each mill in the database by consulting the company's websites and news. To ensure the possibility of redeploying workers *across mills*, we define a business group as an entity with two or more mills in at least one year.

Table 2 shows the distribution of mills by corporate status (standalone or business group). Our main analysis centers on mills opened after 2000 ("new mills"), following the demand boom.[22] Corporate entities—either standalone firms or business groups—in our sample opened a total of 122 new sugar mills during the post-2000 demand boom. Of these, 31 mills were opened by firms with no other sugar mills (*de novo* mills) and 91 mills were opened by business groups with other sugar mills (incumbent mills) at the time of entry. Our analysis of redeployment focuses on mills that belong to business groups rather than standalone mills because only the former can staff positions by redeploying workers from incumbent mills.

4.3 Dependent variable: Worker redeployment

We define worker redeployment as the hiring of a worker who held a position at another mill belonging to the same business group within the previous year.[23] We limit redeployment to job movements that occur between consecutive years and in which a worker moves between

[21] Source: https://www.novacana.com/usinas_brasil. Last accessed on June 15, 2022.

[22] This is aligned with our theory of redeployment as an entry advantage in resource-poor settings, but our findings are consistent when we include all new mills, including any that opened before the year 2000. These supplementary analyses are available from the authors.

[23] In a small number of cases, a worker may hold multiple jobs in a year. Following the literature (e.g., Helpman, Itskhoki, Muendler, & Redding, 2017), in such cases we use the worker's highest paying job in each year.

municipalities to avoid capturing job movements that do not involve the relocation of a worker to a different mill. In worker-level analyses, redeployment is an indicator variable that takes the value one if the worker was hired via redeployment and zero if the worker was hired via the external labor market. In mill-level analyses, we define the variable "redeployment share," which is the number of workers hired via redeployment over all new hires in a mill.

4.4 Independent variable: Labor market thickness

We use the universe of observations in RAIS to measure labor market thickness as the probability of finding workers in each labor market with experience relevant to sugar processing. Specifically, we measure labor market thickness in municipality m as:

$$\lambda_m = \frac{1}{E_m}\sum_{j=1}^{J} S_j E_{jm} \tag{9}$$

where E_{jm} is employment in each industry j, S_j is the similarity of industry j to sugar processing, and E_m is total employment in the municipality. Similarity for each five-digit industry j to sugar processing (which includes sugar cultivation, milling, and refining) is the cosine similarity of their occupation employment shares:

$$S_j = \frac{\sum_{i=1}^{N} v_{ji} v_{si}}{\sqrt{\sum_{i=1}^{N} v_{ji}}\sqrt{\sum_{i=1}^{N} v_{si}}} \tag{10}$$

Above, v_{ji} is the employment share of occupation i in industry j and v_{si} is the employment share of occupation i in sugar cultivation, refining, and milling.

The labor similarity measure is larger when more of a municipality's workers are employed in industries that are more highly related to sugar processing. It mirrors the labor market thickness parameter (λ) in our theory by representing the probability that a randomly selected worker will have experience, and thus skills, relevant to sugar processing. We calculate labor market thickness using data from the year 2000, which predates the widespread adoption of flex-fuel vehicles and subsequent expansion in sugar processing, so that the sugar mills in our sample do not themselves affect the measures. When firms in our sample operate several mills, we measure thickness in the initial market as the average labor market thickness in the municipalities of a firm's pre-existing sugar mills.[24] For each new mill and year, we calculate thickness in the initial market as the average labor market thickness based on all municipalities where the business group had active mills in the prior year.[25] We use this measure in the analysis at the worker level. In the analysis at the mill level, we take the average of this variable across all years.

While the above measure has many desirable properties, we consider three alternative measures of labor market thickness in robustness checks. In the first, we use the share of workers employed in sugar processing, thus assigning a weight ($S_j = 0$) of zero to employment in all other industries in Equation (9). In the second, we measure industry similarity using the Euclidean distance rather than the cosine similarity between industry occupation profiles. In the third, we replace S_j in Equations (9) and (10) with a similarity measure based on observed labor flows between industries as suggested by Neffke & Henning (2013) and Neffke, Otto, & Weyh (2017). We present further details in the online appendix; results using the alternative measures are consistent with those based on Equations (9) and (10).

[24] Thickness in each municipality excludes workers employed in the focal mill. This reflects our interest in the thickness of the *external* labor market. Employment in each municipality and mill is from the year 2000.

[25] Thickness in the initial market is calculated using a leave-out measure excluding the focal mill. For each mill and year, we consider thickness in the municipalities where the group had mills in the prior year, excluding the focal mill.

4.5 Land quality

We measure land quality using the Global Agro-Ecological Zones (GAEZ) database of the Food and Agriculture Organization of the United Nations (FAO). GAEZ uses data on climate, temperature, and soil conditions to measure potential crop yields for 9 km^2 cells.[26] We measure land quality using the 90th percentile of the potential yield for sugarcane—the main input for ethanol production—within a 50-km radius of each mill.[27] We choose this distance because "sugarcane loses its sugar content rapidly after being harvested, limiting sugarcane supply to farms within a 50 km [radius] from the mill" (Sant'Anna et al., 2016). Analogous to our measure of labor market thickness, when firms have multiple mills, we measure initial market land quality by averaging quality across all their pre-existing mills.

4.6 Other variables

We control for municipal level factors in both frontier and initial markets that may influence the redeployment decision. These include the log median monthly real wage, log population, unemployment rate, and log land area. Data come from the 2000 Brazilian Census provided by the Brazilian Institute of Geography and Statistics (IBGE). The unemployment rate is measured as one minus the share of employed persons in the active labor force (persons working or looking for work). For initial markets, we average variables across a firm's pre-existing mills.

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[26] We use the GAEZ version 3.0 data, which at the time of writing, is the latest available version. See http://www.fao.org/nr/gaez/about-data-portal/agricultural-suitability-and-potential-yields/en/

[27] Like Bustos, Caprettini, & Ponticelli (2016), we use the estimates of yield per hectare under the assumption of "high inputs." The GAEZ data expresses yields as estimated output of sugar (in tons per hectare). See p. 42 of Fischer et al. (2021). Global Agro-ecological Zones (GAEZ v4)-Model Documentation. Since sugarcane is likely to be grown on the most suitable land in the vicinity of a mill, we use the 90th percentile value of yield in this 50-km range as our main measure of land quality for each mill.

5 EMPIRICAL ESTIMATION

Our first hypotheses predict that the lower the thickness of the local labor market (*H1a*), and the higher the thickness of a firm's other markets (*H1b*), the more likely the firm is to staff positions via redeployment than via external markets. We initially test *H1a* and *H1b* using the cross-section of new sugar mills opened after 2000. We estimate the following mill-level model:

$$Y_i = \alpha + \beta_1\, Thickness\ Frontier_i + \beta_2\, Thickness\ Initial_i + \alpha_1\, Land\ Frontier_i + \alpha_2\, Land\ Initial_i + \phi' X_i + \gamma_{t(i)} + \epsilon_i \tag{11}$$

Variable Y_i is the redeployment share in mill i, $Thickness\ Frontier_i$ is labor market thickness in the mill's municipality measured in year 2000, $Thickness\ Initial_i$ is the average labor market thickness across all municipalities where the business group has existing mills measured in year 2000, and $Land\ Frontier_i$ and $Land\ Initial_i$ represent land quality for mill i and the firm's existing mills. The vector X_i includes municipality-level controls—median wages, population, land area (all in logarithmic scale), and unemployment rate—in the frontier and initial markets, all measured in the year 2000. We control for population size to isolate the role of labor market *thickness* from the role of labor market *size*. Similarly, we control for area to separate the role of labor market *thickness* from labor market *density* (i.e., the concentration of workers in the geographical area). We also control for the unemployment rate because it may influence the ability to hire workers in external labor markets. Finally, we include a fixed effect for mill opening year ($\gamma_{t(i)}$) to control for general economic conditions and establishment age. According to *H1a* and *H1b*, we predict β_1 to be negative and β_2 to be positive.

We additionally test $H1a$ and $H1b$ at the worker-level, using data on all workers hired in new business group mills. We estimate the following model in which the unit of observation is a hired worker (in the hiring year):

$$Y_{w,i,t} = \beta_1\ Thickness\ Frontier_i + \beta_2\ Thickness\ Initial_i + \alpha_1\ Land\ Frontier_i + \alpha_2\ Land\ Initial_i + \phi' X_i + \gamma_{t(i)} + \tau_t + \epsilon_{w,i,t} \qquad (12)$$

Variable $Y_{w,i,t}$ is a dummy that equals one if worker w is redeployed to mill i in year t from an existing mill of the business group (zero if the worker is hired in the external labor market), and other variables are defined as in Equation (12). $H1a$ predicts $\beta_1 < 0$ and $H1b$ predicts $\beta_2 > 0$.

We next consider if firms are more likely to redeploy workers when output is more sensitive to worker skill (*H2*). Building on research showing the importance of managers for firm growth (Penrose, 1959; Peteraf, 1993) and performance (e.g., Mollick, 2012; Bertrand & Schoar, 2003; Lazear, Shaw, & Stanton, 2015), we examine whether firms are more likely to redeploy managers than other workers by adding a dummy for managers to Equation (12). A positive coefficient indicates that managers are more likely to be redeployed than other workers.[28]

Hypothesis 3 proposes that the relationship between labor market thickness and worker redeployment will be stronger for occupations in which output is more sensitive to worker skill. We test *H3* by running separate regressions for each occupational group—managers, professionals and technicians, agricultural workers, and production workers. *H3* predicts that the coefficient of

[28] In additional analyses (available from the authors), we further explore whether redeployment is positively correlated with observable and unobservable worker attributes. We examine how workers' education, experience, and wages relate to the likelihood of redeployment and find that firms are more likely to redeploy workers with higher levels of education, experience, and wages. We also develop more sophisticated measures of skill using an occupation fixed effect and the dispersion of wage residuals in Mincerian wage regressions. Consistent with *H2*, the results show that these proxies for skill are positively related to redeployment.

labor market thickness will be larger in absolute value for managers than for other workers. We also report regression models that include interaction terms between thickness and a manager dummy variable. In these models, the coefficient for the interaction between the dummy and thickness in the frontier (initial market) should be negative (positive).

Finally, we examine how the quality of a complementary resource—land—shapes the decision to redeploy workers. In our model, the effect of land quality on the benefit of redeployment depends on whether the marginal productivity of skill increases or decreases with the quality of land. Lacking strong priors about the complementarity between worker skill and land quality, we do not make specific predictions about the relationship between land quality and redeployment. We do, however, predict that land quality in the frontier and land quality in the initial market will have opposite effects on redeployment (*H4*). To test *H4,* we compare the sign of the coefficients on land quality in the frontier and initial markets in Equations (11) and (12).

6 RESULTS

Our analysis of redeployment focuses on the 91 new business group mills that could have hired workers via redeployment. Table 3 Panels A–C show summary statistics of the main variables at the mill and worker level, and Table 4 the correlation coefficients.[29] In Table 3 Panel A, the mean redeployment share is 6.4 percent, meaning that new business group mills hire on average 6.4 percent of workers via redeployment. Labor market thickness in the frontier is lower than in the initial market (0.16 versus 0.23), showing that mills founded following the introduction of flex-

[29] The sample in Table 3 Panel A is limited to 91 new business group mills that have the potential to staff positions by redeploying workers from incumbent business group mills. The sample in Table 3 Panel B is limited to all hires (509,764 workers) in these 91 business group mills in their year of hiring. The sample in Table 3 Panel C includes all hires (630,049 workers) in 122 new business group and standalone mills in their year of hiring.

fuel vehicles were in thinner labor markets. Summary statistics at the worker level indicate that the likelihood of redeployment among hired workers is 5.2 percent in new business group mills (Panel B) and 4.2 percent in all new mills—both group and standalone mills (Panel C). Panel C shows that new hires have on average 5.4 years of experience and only 2.5 percent have a college degree. The mean log wage is 7.4 and 81 percent of hires work in mills that belong to business groups. This percentage is higher than the share of new mills belonging to business groups (91/122 = 0.75), suggesting that new business group mills tend to be larger than new standalone mills.

Table 4 provides preliminary evidence about *H1a* and *H1b*. Redeployment share is negatively correlated with thickness in the frontier (-0.15) but positively correlated with thickness in initial markets (0.19). In line with the idea of resource arbitrage, firms appear more likely to redeploy workers when they operate in thicker labor markets and when they enter thinner markets.

Table 5 examines the relationship between redeployment share and labor market thickness in new and initial markets. Models 1–2 report the coefficient estimates of thickness in the frontier market; Models 3–4 report the estimates of thickness in initial markets; Models 5–6 report coefficients for thickness in both frontier and initial markets. Table 5 suggests that, when opening new mills, firms staff more positions via redeployment when the thickness of the new mill's local labor market is lower and when the thickness of their existing mills' labor markets is greater. These results corroborate (*H1a*) and (*H1b*). Model 6 indicates that when thickness in the frontier is one standard deviation (about 13 percentage points) higher, the redeployment share is 3 percentage points lower, which represents a 49 percent decrease in the redeployment share relative to the mean of 6.4 percent. When thickness in the initial market is one standard deviation (about 16 percentage points) higher, the redeployment share is 2.2 percentage points lower; an increase of 34 percent relative to the mean. These magnitudes are economically large and consistent with *H1a* and *H1b*.

Table 6 examines whether the mill-level patterns hold at the worker level. Using data on all hires of new business group mills, we find that labor market thickness in the frontier is associated with a lower likelihood of positions being staffed via inward redeployment, while thickness in initial markets is positively associated with inward redeployment. Consistent with *H1a* and *H1b*, these findings suggest that new business group mills are more likely to staff positions via redeployment when the opportunities for resource arbitrage are greater.

Our model suggests that the quality of complementary inputs (land) may also shape the decision to redeploy workers. While we do not have specific predictions about the sign of the relationship between land quality and redeployment, our model suggests that the coefficients on land quality in the frontier and initial market should be opposite in sign, unless they are both zero (*H4*). Tables 5 and 6 show that firms are more likely to redeploy workers to mills with good land quality and out of mills with poor land quality, evidenced by the positive coefficient on z_N and negative coefficient on z_I. This finding is indicative of a supermodular production function, in which the benefit of high skill workers is greater on higher quality land. These estimates, however, are imprecise, and we cannot rule out a different form for the production function.[30]

Hypothesis 2 predicts that firms are more likely to redeploy workers in occupations in which output is more sensitive to differences in worker skill. To test *H2,* we examine whether new business group mills are more likely to redeploy managers than other workers. Table 7 shows summary statistics of redeployment by occupational group. About 18 percent of managers in new

[30] In additional analyses (available from the authors), we further explore the potential complementarity between land quality and worker skill by investigating whether land quality moderates the relationship between thickness and redeployment. Under a supermodular production function, the negative (positive) relationship between thickness in frontier (initial) markets and redeployment should be stronger on better land in the frontier. We run regressions in which we interact thickness with land quality—in both frontier and initial markets—and do not find support for a supermodular nor submodular production function. While one could conclude that production functions in our context are neither, the estimates are imprecise.

mills are redeployed from other mills, a figure that is higher than the one for professionals and technicians (7 percent), and agricultural and production workers (5 percent). These findings offer preliminary evidence consistent with *H2*.

Table 8 examines *H2* in a regression framework and reports coefficients from regressions predicting redeployment as a function of occupational group dummies. Models 1–2 include only an indicator for managers, while Models 3–4 include indicators for managers, professionals and technicians, and production workers (agricultural workers are the omitted category). Consistent with *H2*, managers are 13.7 percentage points more likely to be redeployed than other workers (Model 2). Models 3–4 show that professionals and technicians (such as engineers) are also more likely to be redeployed than agricultural workers. Together, these results corroborate *H2* that redeployment is more likely when differences in worker skill have greater influence on output.

We next examine whether sensitivity to worker skill moderates the relationship between labor market thickness and redeployment (*H3*). Table 9 reports coefficient estimates of Equation (12) for different samples of workers. We report the estimates of thickness in frontier and initial markets for managers (Models 1–2), professionals and technicians (Models 3–4), agricultural workers (Models 5–6), and production workers (Models 7–8). *H3* predicts that estimates for thickness in the frontier and initial markets will be greater in magnitude (more negative for thickness in the frontier and more positive for thickness in the initial market) for managers than other workers. Consistent with *H3*, Table 9 shows that the coefficient on labor market thickness in frontier and initial markets is greater in magnitude for managers than for other workers. The coefficient for thickness in the frontier is about 3.7 (-0.52/-0.14) times larger for managers than for agricultural workers. The difference is also large for thickness in initial markets: the coefficient for thickness in the initial markets is 5.2 times higher for managers than for agricultural workers.

This suggests that the effect of labor market thickness is stronger in occupations in which output is more sensitive to differences in worker skill (*H3*).

We also examine *H3* by including interaction terms between the thickness measures (in the frontier and initial markets) and an indicator for managers. Table 10 reports coefficient estimates. Thickness in the frontier is negatively related to redeployment (*H1a*), and this negative relationship is stronger for managers than for other workers (*H3*). This is shown by the negative coefficient in Column 6 on *Managers* × *Thickness* in the frontier (-0.40). Thickness in the initial market is positively related to redeployment (*H1b*) and is stronger for managers than other workers. In Column 6, the coefficient on *Managers* × *Thickness* in the initial market is positive but imprecisely estimated (0.18). These findings are consistent with *H3*.

6.1 Analysis of entry advantages from redeployment

So far, our findings show that firms redeploy workers to new markets and do so more intensively when these markets are resource scarce, and their existing markets are resource rich. The capability to overcome resource scarcity in frontier markets via redeployment may provide business groups with entry advantages over firms without redeployment capabilities. To explore these advantages, we first examine if redeployed workers are indeed higher-skilled than workers hired in external markets by comparing their experience, educational attainment, and wages (as a proxy for skill level) to that of external hires. Table 11 shows results from regressions of log experience, college degree, and log wage on indicators for whether a mill belongs to a business group and whether a worker is redeployed. While business groups do not have advantages over standalone firms in hiring higher-skilled workers via external markets—as evidenced by the small and statistically insignificant coefficients for the business group dummy in Columns 1, 3, and 5—business groups' *redeployed* workers have more experience, higher educational attainment, and higher skill (proxied by higher wages) than external hires, even when compared to workers in the same occupation and mill (see Columns 2, 4, and 6). Higher levels of experience, education, and skill among employees can offer advantages for new business group mills relative to standalone mills.

We also investigate if business groups have an advantage over standalone firms in setting up larger enterprises. We shed light on this advantage by examining whether business group mills are larger than standalone mills in the early years of operation. Table 12 reports separate regressions of mill size (log workers) on a business group dummy for each of the first five years since opening. Column 1 shows that business group mills are 2.6 times larger than standalone mills in their opening year ($e^{1.273} - 1 = 2.6$). This difference shrinks over time but is still large in year 5 ($e^{0.434} - 1 = 0.5$). Consistent with our theory, redeployment allows firms to grow larger in initial years, showing a benefit of redeployment that is realized at the time of entry rather than exit.

6.2 Alternative explanations and robustness tests

We consider several alternative explanations and examine the robustness of the findings to different empirical choices. Our theory posits that firms redeploy workers from existing businesses to overcome resource scarcity when entering new markets. An alternative explanation is that firms redeploy workers out of troubled or failing businesses (e.g., Lieberman et al., 2017; Santamaria, 2021). We examine this possibility by investigating employment patterns of *incumbent mills* before and after the opening of a new mill in the business group.

We use a difference-in-differences approach that compares incumbent mills in business groups that opened a new mill to incumbent mills in business groups that did not, before and after the opening of the mill.[31] Using mill-year level models with mill and year fixed effects, we analyze how the opening of a new mill influences outward redeployment, hiring, and total employment in incumbent mills of the same group. This empirical approach isolates persistent differences across mills or common shocks from differences that emerge after the opening of a new mill in the group. To examine the assumption of parallel trends—whether incumbent mills in business groups that opened a new mill and those in groups that did not follow similar trends before the opening of the mill—and learn about the temporal dynamics after the mill opening, we plot estimates of event time dummies 8 years before and after mill opening. Figure 5 shows the dynamics of outward redeployment, hiring, and total employment respectively.[32]

Figure 5a shows that, before the opening of a new mill, incumbent mills in business groups that opened a new mill do not redeploy more workers out than mills in business groups that did open a new mill. After opening a new mill, however, incumbent mills in the same business group redeploy more workers than other mills. Outward redeployment increases at the time of mill opening and remains higher for at least three years. These findings corroborate the idea that redeployment is triggered by expansion rather than the decline of an existing business.

To further rule out the possibility that troubled or failing mills drive outward redeployment, we examine hiring and employment in incumbent mills around the opening of a new mill. Figures 5b–c show that incumbent mills in business groups that open a new mill do not hire fewer workers or reduce their workforce relative to incumbent mills in other business groups. There seems to be an increase in hiring and employment size after the opening of a new mill, though estimates are imprecise. There is no evidence that incumbent mills in business groups that open a

[31] To identify the dynamics around mill opening more cleanly and avoid the confluence of multiple treatments, the analysis focuses on business groups that opened exactly one mill during the sample period.

[32] We present the estimates for the difference-in-differences regressions in the online appendix.

new mill are failing or exiting, which helps rule out the alternative explanation that redeployment is triggered by distress in initial markets.

Additional analyses, reported in the online appendix, show that wages for redeployed workers follow an upward trajectory before and after a redeployment episode, which further corroborates our claim that firms are not redeploying workers out of failing businesses.[33] Redeployed workers appear to benefit from redeployment by experiencing both an immediate wage increase and subsequent wage increases for several years post-redeployment.[34]

Relatedly, redeployment does not seem to be purely temporary.[35] The average worker tenure in new business group mills is 2.4 years and is similar for redeployed and non-redeployed workers. A survival analysis controlling for mill, starting year, and occupational group, shown in the online appendix, indicates that redeployed workers stay longer in their job. Thus, redeployment in our setting is not driven solely by the need to jumpstart operations or train local workers.

Next, we examine the generalizability of the findings to alternative measures of labor market thickness. We create three alternative measures: (a) the share of employment in sugar in a municipality in 2000, (b) the share of employment in related industries based on the Euclidean distance between industries, and (c) the share of employment in related industries based on labor

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[33] Wages for cohort workers—workers with the same occupation, education level, and age that join the same business group in the same state and year—also trend upwards, suggesting that firm and worker productivity is increasing.

[34] We show that wages for redeployed workers and cohort workers are similar upon joining the business group and follow a similar upward trajectory leading up to redeployment. The wages of redeployed workers increase sharply after redeployment. The difference between wages of redeployed and cohort workers soars upon redeployment and increases for several years post-redeployment.

[35] Employees, particularly high-skilled workers, could be temporarily redeployed to new mills to get the new operation running and train other employees. This is an additional benefit of redeployment that, though not incorporated in our model, would make redeployment to new mills more attractive. Our theory indicates that redeployment can be a valuable strategy even in absence of skill development and learning.

flows between industries. The main findings of the paper are robust to these alternative measures of labor market thickness (see the online appendix for details and results).

Finally, we consider the sensitivity of the findings to different geographical definitions of labor markets. Our main definition uses municipal boundaries to calculate the share of workers in related industries. We explore alternatives that consider all municipalities within a radius of 20 and 50 km from the focal municipality.[36] Mill-level regressions show that the negative relationship between redeployment and thickness in the frontier fades as we expand the geographic boundaries of labor markets (see online appendix). Compared with municipal boundaries, we find a negative but weaker relationship between redeployment share and thickness within 20 km and no statistically significant relationship within 50 km. This pattern corroborates the fact that sugar activity concentrates in close proximity to mills (Sant'Anna et al., 2016), and also suggests that unobserved regional factors correlated with thickness do not drive our results.

7 CONCLUSION

A growing body of work shows that resource redeployment—the act of withdrawing a resource from one activity and using it in another within a firm—is positively associated with corporate value (Folta et al., 2016; Sakhartov & Folta, 2014). While research has emphasized the benefits of redeployment across product markets with different levels of profitability (Dickler & Folta, 2020; Sakhartov & Folta, 2015; Stagni, Santalo, & Giarratana, 2016), less is known about value-creation from redeployment across factor markets with different degrees of resource munificence. Using data on the population of sugar mills in Brazil, the world's largest producer and exporter of sugar,

[36] Specifically, we identify all municipalities within 20 km (50 km) from the centroid of the focal municipality and calculate thickness using the sum of workers across these municipalities.

we show how the capability to redeploy skilled human capital to new mills via internal labor markets provides entry advantages to incumbent relative to *de novo* firms in the industry. Empirically, we show that entry triggers redeployment to new mills and away from incumbent ones and, consistent with our focus on resource scarcity, that firms redeploy more intensively, the thinner the local labor market in which the new mill operates, and the thicker the labor markets of the firms existing units. We present descriptive evidence that corroborates the view that redeployment endows incumbent firms with entry advantages relative to *de novo* firms, including larger size and higher levels of human capital.

This study contributes to the resource redeployment literature by developing a theoretical framework that highlights differences in resource scarcity across strategic factor markets (Barney, 1991; 1986; Mackey, Molloy, & Morris, 2014; Makadok & Barney, 2001; Peteraf, 1993) as a new and important determinant of resource redeployment decisions. We propose that when factor markets are local and exhibit varying resource scarcity, firms can benefit from internally redeploying resources from markets where they are more abundant to where they are scarce. Interestingly, in the mechanism that we highlight, the internal opportunity cost of resources (Levinthal, 2017; Levinthal & Wu, 2010) results not from differences in resource *returns* across a firm's units but differences in their cost of resource *acquisition* (Makadok, 2001; Maritan & Lee, 2017; Maritan & Peteraf, 2011), with the joint exercise of firms' resource acquisition and resource redeployment capabilities leading to value-creation. One important implication of this mechanism is that the redeployment option is valuable beyond the context of diversified firms and for any firm that is active across multiple factor markets. More broadly, it indicates that beyond participation in multiple product markets (Anand & Sinh, 1997; Wu, 2013; Sohl & Folta, 2019; Giarratana & Santaló, 2020; Dickler & Folta, 2021; Chang & Matsumoto, 2022; Bodner, 2022), involvement in multiple factor markets can also endow firms with resource redeployment advantages. Resource redeployment gives firms valuable arbitrage opportunities that exist "not because the arbitrage is complex per se, or because of a lack of inventive genius, but because its feasibility was simply hidden by market incompleteness" (Denrell, Fang, & Winter, 2003: 981).

We also contribute to the literature on firm entry, especially research on entry advantages from resource redeployment (Lieberman et al., 2017; Belenzon et al., 2018; Santamaria 2021). Relative to prior studies, we highlight a new source of entry advantage from higher productivity at entry rather than lower sunk costs, which has implications for the performance of new ventures in firms with redeployment capabilities. Like lower sunk costs, higher productivity at entry indicates that firms with redeployment capabilities can enter more markets (Hopenhayn, 1992; Melitz, 2003). Additionally, our framework implies that conditional on entry into the same market, the expected performance of firms with redeployment capabilities is *higher* than that of other firms. Hence, we propose a novel mechanism that helps firms take advantage of new opportunities rather than moving workers from units affected by adverse shocks to those with better prospects (Faccio & O'Brien, 2021; Huneeus, Huneeus, Larrain, Larrain, & Prem, 2021; Tate & Yang, 2015).

In identifying this new source of entry advantage, we also connect the literature on entry and redeployment to the literature on industry evolution and industry dynamics, which has documented the conditions under which incumbent firms tend to outperform startups (Agarwal & Gort, 1996; Balasubramanian, 2011; Balasubramanian & Lieberman, 2010; Chen, Williams, & Agarwal, 2012; Ganco & Agarwal, 2009). These performance differences have typically been attributed to superior operating and organizational learning capabilities (e.g., Balasubramanian 2011). We highlight differences in the quality of factors of production as another mechanism that can lead to an incumbent advantage. A novel implication of this mechanism, reflected in our data, is that incumbents are especially likely to outperform startups when business opportunities arise in locations with underdeveloped factor markets. This is consistent with Chang & Wu (2014), who document a similar pattern when the institutional environment is underdeveloped.

We also contribute to the literature on business groups by incorporating opportunity and redeployment costs into the redeployment decision. Research has emphasized how business groups fill institutional voids by developing internal factor markets (Khanna & Palepu, 2000; Khanna & Yafeh, 2007). While this work highlights the benefits of resource sharing, it does not extensively consider the opportunity costs of non-scale free resources (e.g., managers)—although withdrawing resources from existing businesses can dampen their performance (Mingo, 2013). By incorporating opportunity and redeployment costs, our study reveals *when* business groups are more likely to redeploy resources, namely when they enter resource-scarce markets, and enjoy low cost of resource replacement and low redeployment costs. Thus, we help to identify the mechanisms that give rise to performance advantages of business groups vis-à-vis standalone firms: the capability to arbitrage resources across factor markets (e.g., Berry & Kaul, 2022) and identify unique opportunities hidden by imperfect factor markets (e.g., Manikandan & Ramachandran, 2015).

Finally, we answer the call for research to provide "direct observations of redeployments" (Folta et al., 2016: 20) in order to gain clarity on when redeployment is used and to test key aspects of redeployment theory. Until recently, direct observation of resource redeployment has been limited; the increasing availability of employee-employer matched datasets (e.g., Bodner, 2022; Chauvin & Poliquin, 2020) and microdata on worker mobility (e.g., Karim & Williams, 2012; Stadler, Helfat, & Verona, 2021) has enabled researchers to provide direct evidence on the use of worker redeployment that can be compared across contexts. Our results showing that new plant openings trigger redeployment are consistent with a similar fact documented by Cestone, Pica, Fumagalliz, & Kramarz (2020) in the context of France, though the mechanism (insurance for workers vs. resource scarcity) that each paper highlights differs. Our findings that redeployment is more intensively used for workers at higher levels of the hierarchy corroborate the focus on top managers, such as in Belenzon and Tsolmon (2016). Our theorizing on how a complementary input—land—affects the redeployment of a focal resource also relates to papers discussing redeployment decisions with multiple factors of production (Belenzon & Tsolmon, 2016; Belenzon et al., 2019). However, while these research studies focus on the implications of factor substitutability, we explore the implications of factor complementarity for redeployment. A unique contribution of our paper relative to existing empirical studies is to document differences in factor market resource scarcity as an important determinant of redeployment.

We note several limitations of our study that underscore opportunities for future research. By design, our study is confined to one industry. This allows us to cleanly identify an impetus for new plant openings largely exogenous to the firms in our sample but limits the generalizability of our findings. An opportunity for future research is to document patterns of resource scarcity and redeployment across different industry contexts. It would be useful to establish whether the nature of this advantage depends on the type of human capital required by an industry (e.g., high- versus low-skilled, industry-specific versus general).

Additionally, we observe the redeployment of one resource—human capital. It would be fruitful for future empirical studies to consider the joint redeployment of multiple resources. For example, Giroud & Mueller (2014) find evidence of capital and labor reallocation among firm units, but only for financially constrained firms. It would likewise be useful to explore to what extent the entry advantages that we document are moderated by the availability of financial capital.

Finally, we consider practical implications of our work for managers and policymakers. From a managerial perspective, our study indicates that prior operating experience in a strategic factor market and investments to gather information about resources available in different factor markets can endow firms with redeployment capabilities that they can monetize as they enter new markets. Thus, we provide another answer to Makadok and Barney's (2001) question about what "kinds of information firms should acquire in order to obtain the resources they need to develop competitive advantage" (p. 1622); namely, information about resource availability in different factor markets. We also highlight how serendipity—"effort and luck joined by alertness and flexibility" (Denrell, Fang, & Winter, 2003: 978)—can help firms discover valuable strategic opportunities. Policymakers worldwide have put significant efforts toward developing new industries and encouraging entrepreneurship, especially in disadvantaged regions—at times experiencing failure due to an absence of well-developed local factor markets. Our study indicates that relative to de novo firms, incumbent firms leveraging internal redeployment capabilities can accelerate regional development as suitable opportunities arise.

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TABLES

Table 1. Third-period profits for incumbent with a high-skill worker following entry in the frontier

	Without redeployment	With redeployment
Frontier market	$p_N[\lambda_N f_H(z_N) + (1-\lambda_N) f_L(z_N)] - w_N - F_N$	$p_N f_H(z_N) - w_I - F_N - R$
Initial market	$p_I f_H(z_I) - w_I$	$p_I[\lambda_I f_H(z_I) + (1-\lambda_I) f_L(z_I)] - w_I$

Table 2. Sample of new and incumbent mills by business group status

	Standalone	Business group	Total
Incumbent mills (active in 2000)	150	173	323
New mills (enter after 2000)	31	91	122
Total	181	264	445

Notes: Authors' calculations using data from RAIS, the registry of sugar mills maintained by the Ministry of Agriculture and the National Petroleum Agency, and NovaCana. Table shows business group status in 2000 for incumbent mills and business group status in the opening year for new mills. The table does not include 14 standalone mills and 4 business group mills that exited the market before 2000.

Table 3. Summary statistics

Panel A. Mill level (New business group mills)

Variable	Mean	SD	Percentiles 25th	50th	75th
Redeployment share	0.06	0.09	0.01	0.03	0.08
Thickness in frontier	0.16	0.13	0.07	0.11	0.19
Thickness in initial market	0.23	0.16	0.15	0.22	0.32
Wages in frontier (2000 R$)	5.60	0.19	5.52	5.65	5.70
Wages in initial market (2000 R$)	5.71	0.22	5.60	5.72	5.86
Land quality in frontier (sugar ton/ha)	2.20	0.14	2.16	2.20	2.27
Land quality in initial market (sugar ton/ha)	2.23	0.11	2.19	2.24	2.28

Notes: N = 91. Sample is limited to new business group mills. Wage is the municipality's median monthly wage in 2000 (in Brazilian Reais). Wages and land quality are in logarithmic scale.

Panel B. Worker level (New business group mills)

Variable	Mean	SD	Percentiles 25th	50th	75th
Worker was redeployed, dummy	0.05	0.22	0.00	0.00	0.00
Thickness in frontier	0.17	0.14	0.07	0.11	0.19
Thickness in initial market	0.24	0.15	0.15	0.24	0.33
Wages in frontier (2000 R$)	5.61	0.19	5.52	5.70	5.70
Wages in initial market (2000 R$)	5.71	0.24	5.62	5.74	5.86
Land quality in frontier (sugar ton/ha)	2.21	0.11	2.16	2.19	2.27
Land quality in initial market (sugar ton/ha)	2.24	0.08	2.21	2.25	2.28

Notes: N = 509,780. Sample includes all workers in new business group mills. Wage is the municipality's median monthly wage in 2000 (in Brazilian Real). Wages and land quality are in logarithmic scale.

Panel C. Worker level (New business group and standalone mills)

Variable	Mean	SD	Percentiles 25th	50th	75th
Worker was redeployed, dummy	0.04	0.20	0.00	0.00	0.00
Experience (years)	5.43	4.44	2.00	4.00	8.00
Higher education, dummy	0.03	0.16	0.00	0.00	0.00
Log wage (2008 R$)	7.44	0.56	7.10	7.42	7.75
Business group, dummy	0.81	0.39	1.00	1.00	1.00

Notes: N = 630,074. Sample includes all workers in new business group and standalone mills. Wage is the worker's average monthly wage (in 2008 Brazilian Real).

Table 4. Correlation coefficients

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Redeployment share	1.00						
(2) Thickness in frontier (λ_N)	-0.15	1.00					
(3) Thickness in initial market (λ_I)	0.18	0.07	1.00				
(4) Wages in frontier (w_N)	0.04	-0.01	-0.09	1.00			
(5) Wages in initial market (w_I)	-0.01	-0.09	-0.05	0.47	1.00		
(6) Land quality in frontier (z_N)	0.02	0.14	0.15	0.25	0.07	1.00	
(7) Land quality in initial market (λ_I)	-0.01	0.02	0.24	0.08	0.36	0.52	1.00

Notes: N = 91. Sample is limited to new business group mills. Wages and land quality are in logarithmic scale.

Table 5. Labor market thickness and redeployment (mill-level results)

DV = Redeployment share	(1)	(2)	(3)	(4)	(5)	(6)
Thickness in frontier (λ_N)	-0.114	-0.248			-0.124	-0.249
	(0.050)	(0.087)			(0.051)	(0.081)
Thickness in initial market (λ_I)			0.109	0.133	0.115	0.134
			(0.058)	(0.083)	(0.058)	(0.077)
Wages in frontier (w_N)		0.021		0.027		0.030
		(0.060)		(0.054)		(0.057)
Wages in initial market (w_I)		0.014		0.021		0.027
		(0.067)		(0.065)		(0.067)
Land quality in frontier (z_N)		0.130		0.075		0.137
		(0.103)		(0.096)		(0.098)
Land quality in initial market (z_I)		-0.276		-0.240		-0.315
		(0.244)		(0.247)		(0.242)
Control variables		●		●		●
Opening year fixed effect		●		●		●
Observations	91	91	91	91	91	91
R^2	0.023	0.271	0.034	0.226	0.062	0.303

Notes: The unit of observation is a sugar/ethanol mill. The dependent variable is the share of workers hired via redeployment (over all hires in the mill). Columns (2), (4), and (6) include controls (log population, log area, unemployment rate) for both the origin and destination municipality and mill opening year fixed effects. Sample is limited to 91 mills that belonged to business groups and were inaugurated after 2000. Robust standard errors in parentheses.

Table 6. Labor market thickness and redeployment (worker-level results)

DV = Worker was redeployed (0/1)	(1)	(2)	(3)	(4)	(5)	(6)
Thickness in frontier (λ_N)	-0.076	-0.126			-0.071	-0.124
	(0.030)	(0.040)			(0.029)	(0.037)
Thickness in initial market (λ_I)			0.071	0.098	0.066	0.096
			(0.043)	(0.050)	(0.043)	(0.048)
Wages in frontier (w_N)		0.024		0.022		0.025
		(0.039)		(0.037)		(0.036)
Wages in initial market (w_I)		0.016		0.015		0.024
		(0.036)		(0.034)		(0.034)
Land quality in frontier (z_N)		0.026		-0.007		0.046
		(0.059)		(0.056)		(0.056)
Land quality in initial market (z_I)		-0.159		-0.162		-0.213
		(0.129)		(0.135)		(0.133)
Control variables		●		●		●
Opening year fixed effect		●		●		●
Year fixed effects	●	●	●	●	●	●
Observations	509,780	509,780	509,780	509,780	509,780	509,780
R^2	0.009	0.022	0.009	0.021	0.011	0.025

Notes: Observations are newly hired workers. Columns (2), (4), and (6) include controls (log population, log area, unemployment rate) for both the origin and destination municipality and mill opening year fixed effects. Sample is limited to 509,780 new hires in 91 mills that belonged to business groups opened after 2000. Robust standard errors clustered at the mill-level in parentheses.

Table 7. Occupation, education, wage, experience, and redeployment

	Mean	SD	Observations
Occupation			
Managers	0.18	0.38	2,077
Professionals and technicians	0.07	0.25	42,918
Agricultural workers	0.05	0.22	328,072
Production workers	0.05	0.21	136,709
Education			
No college degree	0.05	0.22	496,835
College degree	0.12	0.32	12,943
Wage			
Bottom tercile	0.03	0.17	170,052
Middle tercile	0.05	0.22	169,826
Top tercile	0.08	0.27	169,902
Experience			
Bottom tercile	0.02	0.13	178,057
Middle tercile	0.06	0.24	167,987
Top tercile	0.08	0.28	163,736

Notes: This table shows the mean and standard deviation of redeployment (a dummy indicating that the worker was hired via redeployment) by occupation, education, wage, and experience. Terciles of wage and experience are created within the sample of all workers in new business group mills.

Table 8. Occupation and redeployment

DV = Worker was redeployed (0/1)	(1)	(2)	(3)	(4)
Managers	0.128	0.137	0.129	0.137
	(0.027)	(0.024)	(0.027)	(0.024)
Professionals and technicians			0.017	0.018
			(0.007)	(0.005)
Production workers			-0.003	-0.007
			(0.006)	(0.006)
Thickness in frontier (λ_N)		-0.126		-0.127
		(0.037)		(0.037)
Thickness in initial market (λ_I)		0.096		0.098
		(0.048)		(0.048)
Wages in frontier (w_N)		0.026		0.025
		(0.036)		(0.036)
Wages in initial market (w_I)		0.024		0.026
		(0.034)		(0.034)
Land quality in frontier (z_N)		0.045		0.044
		(0.056)		(0.056)
Land quality in initial market (z_I)		-0.213		-0.217
		(0.133)		(0.134)
Control variables		●		●
Opening year fixed effect		●		●
Year fixed effect	●	●	●	●
Observations	509,776	509,776	509,776	509,776
R^2	0.008	0.027	0.009	0.027

Notes: The unit of observation is a hired worker in the hiring year. The dependent variable is a dummy indicating that the worker was hired via redeployment. Columns (2) and (4) include controls (log population, log area, unemployment rate) for both the origin and destination municipality and mill opening year fixed effects. The omitted occupational category in Column (4) is agricultural workers. Sample is limited to 509,776 new hires in 91 mills that belonged to business groups and were inaugurated after 2000. Robust standard errors clustered at the mill-level in parentheses.

Table 9. Occupation, labor market thickness, and redeployment

DV = Worker was redeployed (0/1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Managers		Professionals and technicians		Agricultural workers		Production workers	
Thickness in frontier (λ_N)	-0.510	-0.519	-0.065	-0.106	-0.074	-0.141	-0.066	-0.087
	(0.136)	(0.124)	(0.033)	(0.038)	(0.032)	(0.042)	(0.030)	(0.036)
Thickness in initial market (λ_I)	0.348	0.444	0.126	0.157	0.058	0.086	0.070	0.114
	(0.144)	(0.149)	(0.054)	(0.062)	(0.044)	(0.049)	(0.051)	(0.055)
Wages in frontier (w_N)		0.196		-0.020		0.029		0.028
		(0.111)		(0.044)		(0.041)		(0.035)
Wages in initial market (w_I)		-0.066		0.015		0.040		-0.010
		(0.140)		(0.040)		(0.040)		(0.030)
Land quality in frontier (z_N)		0.138		0.049		0.055		0.031
		(0.188)		(0.046)		(0.073)		(0.046)
Land quality in initial market (z_I)		-0.308		-0.262		-0.198		-0.236
		(0.514)		(0.143)		(0.155)		(0.133)
Control variables		●		●		●		●
Opening year fixed effect		●		●		●		●
Year fixed effect	●	●	●	●	●	●	●	●
Observations	2,077	2,077	42,918	42,918	328,072	328,072	136,709	136,709
R^2	0.088	0.147	0.011	0.029	0.012	0.029	0.016	0.032

Notes: The unit of observation is a hired worker in the hiring year. The dependent variable is a dummy indicating that the worker was hired via redeployment. Columns (2), (4), (6), and (8) include controls (log population, log area, unemployment rate) for both the origin and destination municipality and mill opening year fixed effects. Sample is limited to managers in columns 1-2, professionals and technicians in columns 3-4, agricultural workers in columns 5-6, and production workers in columns 7-8. Robust standard errors clustered at the mill-level in parentheses.

Table 10. Occupation, labor market thickness, and redeployment

DV = Worker was redeployed (0/1)	(1)	(2)	(3)	(4)	(5)	(6)
Managers	0.228	0.221	0.097	0.096	0.194	0.183
	(0.039)	(0.037)	(0.031)	(0.030)	(0.039)	(0.037)
Thickness in frontier (λ_N)	-0.075	-0.126			-0.070	-0.124
	(0.030)	(0.040)			(0.029)	(0.037)
Thickness in initial market (λ_I)			0.071	0.098	0.065	0.096
			(0.043)	(0.050)	(0.043)	(0.047)
Managers × Thickness in frontier (λ_N)	-0.438	-0.383			-0.454	-0.401
	(0.129)	(0.122)			(0.135)	(0.128)
Managers × Thickness in initial market (λ_I)			0.137	0.156	0.168	0.180
			(0.125)	(0.118)	(0.136)	(0.130)
Wages in frontier (w_N)		0.024		0.022		0.026
		(0.039)		(0.037)		(0.036)
Wages in initial market (w_I)		0.016		0.015		0.024
		(0.036)		(0.034)		(0.034)
Land quality in frontier (z_N)		0.025		-0.009		0.045
		(0.059)		(0.056)		(0.056)
Land quality in initial market (z_I)		-0.158		-0.161		-0.213
		(0.129)		(0.135)		(0.133)
Control variables		●		●		●
Opening year fixed effect		●		●		●
Year fixed effect	●	●	●	●	●	●
Observations	509,776	509,776	509,776	509,776	509,776	509,776
R^2	0.011	0.024	0.010	0.022	0.013	0.027

Notes: The unit of observation is a hired worker in the hiring year. The dependent variable is a dummy indicating that the worker was hired via redeployment. Columns (2), (4), and (6) include controls (log population, log area, unemployment rate) for both the origin and destination municipality and mill opening year fixed effects. Sample is limited to 509,776 new hires in 91 mills that belonged to business groups and were inaugurated after 2000. Robust standard errors clustered at the mill-level in parentheses.

Table 11. Redeployment and worker characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
DV =	Log experience		College degree (0/1)		Log wage	
Business group	-0.065		0.002		0.014	
	(0.040)		(0.002)		(0.031)	
Inward redeployment	0.525	0.571	0.022	0.022	0.174	0.197
	(0.031)	(0.028)	(0.004)	(0.005)	(0.018)	(0.019)
Female	-0.441	-0.441	0.025	0.024	-0.261	-0.248
	(0.020)	(0.018)	(0.003)	(0.003)	(0.010)	(0.008)
Education:						
Elementary	-0.023	-0.035			0.030	0.027
	(0.018)	(0.015)			(0.018)	(0.012)
Some middle school	-0.071	-0.067			0.008	0.032
	(0.015)	(0.015)			(0.015)	(0.010)
Middle school	-0.050	-0.059			0.059	0.065
	(0.022)	(0.019)			(0.020)	(0.012)
Some high school	-0.232	-0.247			0.009	0.029
	(0.022)	(0.021)			(0.016)	(0.012)
High school	-0.046	-0.059			0.115	0.143
	(0.022)	(0.022)			(0.018)	(0.013)
Some higher education	-0.078	-0.081			0.183	0.200
	(0.028)	(0.027)			(0.017)	(0.015)
Higher education	0.221	0.200			0.786	0.801
	(0.026)	(0.026)			(0.028)	(0.026)
Log experience			0.008	0.008	0.120	0.118
			(0.001)	(0.001)	(0.004)	(0.004)
Opening year fixed effect	●	●	●	●	●	●
Year fixed effect	●	●	●	●	●	●
Occupation fixed effect	●	●	●	●	●	●
State fixed effect	●		●		●	
Mill fixed effect		●		●		●
Mean DV	1.317	1.317	0.025	0.025	7.436	7.436
Observations	630,070	630,070	630,070	630,070	630,070	630,070
R^2	0.113	0.132	0.159	0.162	0.401	0.434

Notes: The unit of observation is a hired worker in the hiring year. This table shows estimates of regressions of worker attributes on dummies for business group and inward redeployed workers. The dependent variable is log experience in columns 1-2, college degree in columns 3-4, and log wage in columns 5-6. Regressions in Columns 1, 3, and 5 include opening year, calendar year, occupation, and state fixed effects. Regressions in Columns 2, 4, and 6 include opening year, calendar year, occupation, and mill fixed effects. Experience is the number of work years (including in the current work year), college degree is a dummy for whether the worker has college degree, and wage is the current monthly wage. The coefficient of business group is dropped in Columns 2, 4, and 6 because the business group dummy is colinear to mill fixed effects. Robust standard errors clustered at the mill-level in parentheses.

Table 12. Mill size of business group and standalone mills

DV = Log workers	(1)	(2)	(3)	(4)	(5)
	Opening year	Year 2	Year 3	Year 4	Year 5
Business group	1.273	1.134	0.704	0.593	0.434
	(0.423)	(0.290)	(0.264)	(0.308)	(0.296)
Control variables	●	●	●	●	●
Opening year fixed effect	●	●	●	●	●
Observations	121	120	119	120	119
R^2	0.181	0.210	0.186	0.143	0.138

Notes: The unit of observation is a sugar/ethanol mill. Table shows estimates from separate regressions of mill size (log workers) t years after opening on a dummy for business group. Regressions include controls (log median wage, log land quality, log population, log area, unemployment rate) for the destination municipality and opening year fixed effects. Sample consists of 121 new mills—both standalone and business group mills—inaugurated after 2000. Robust standard errors in parentheses.

FIGURES

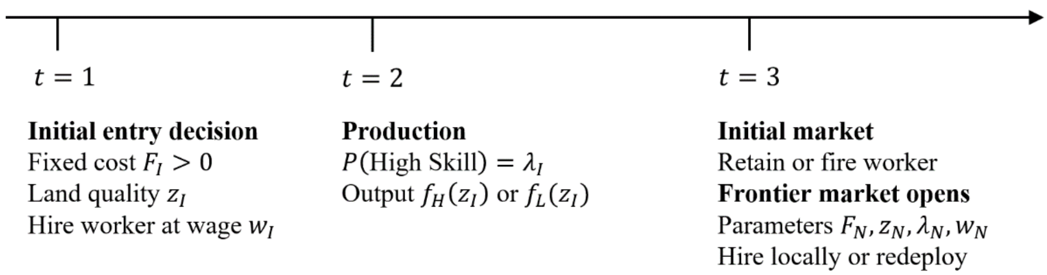
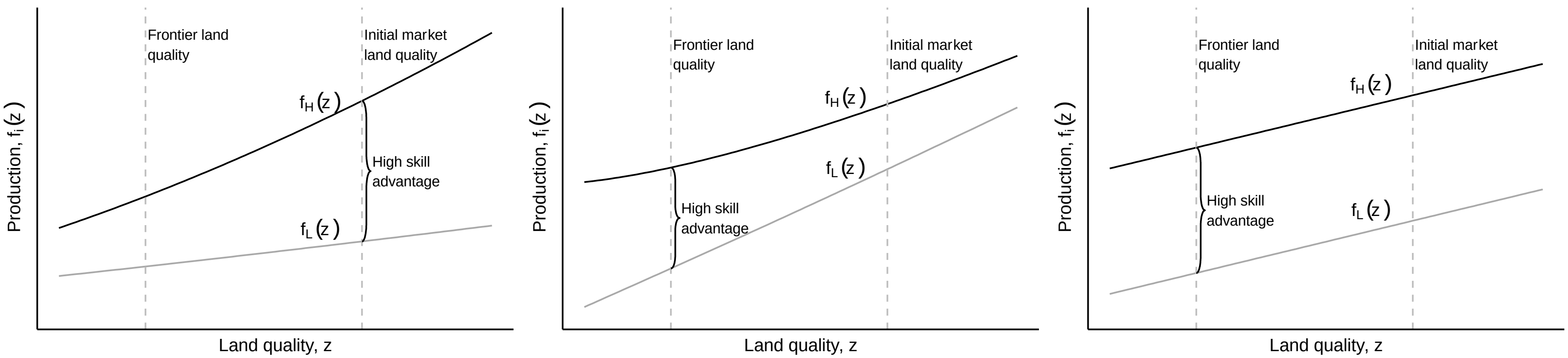
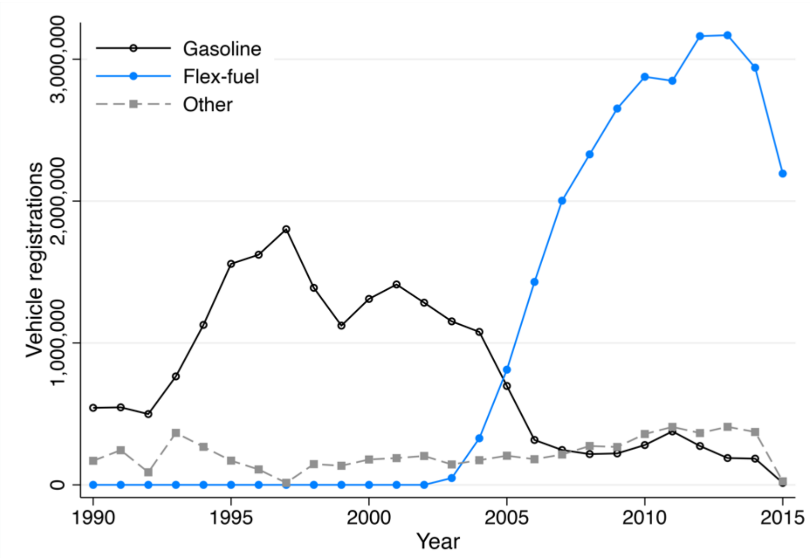


Figure 1. Production timeline



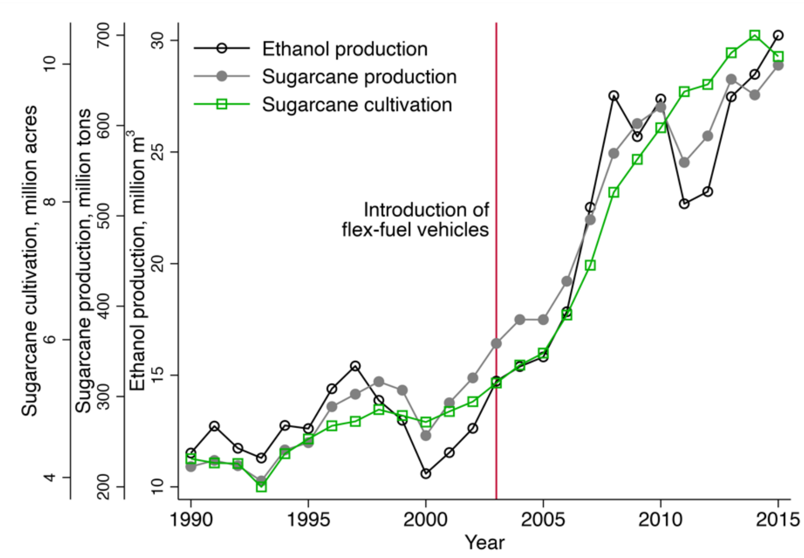
(a) Greater advantage on high-quality land (b) Greater advantage on low-quality land (c) Constant advantage

Figure 2. The advantage of a high-skill worker



Note: Data from Brazilian Automotive Industry Association (2020).
Other category includes ethanol-only, electric, and diesel vehicles.

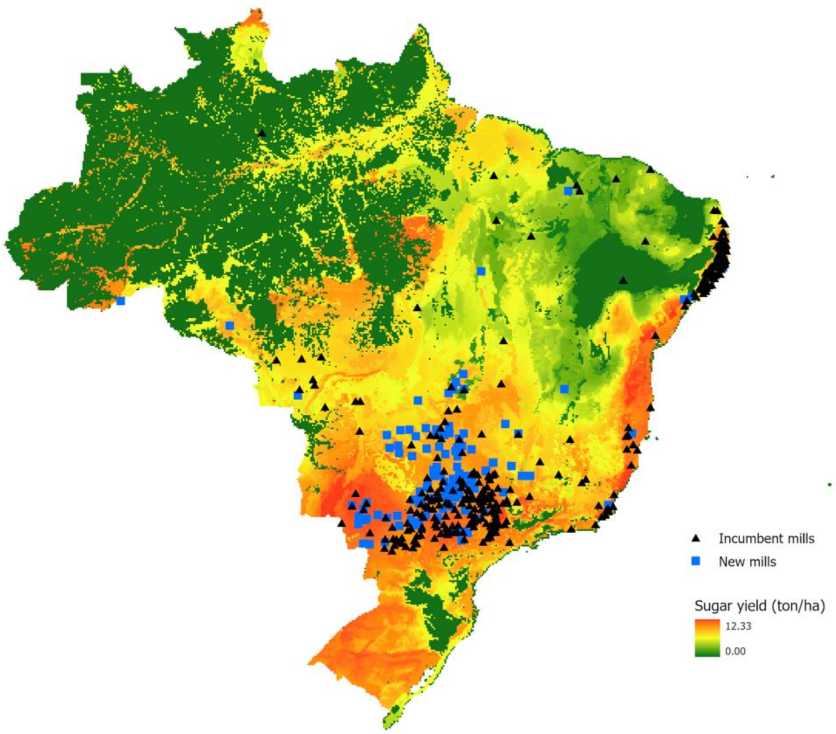
(a) New vehicle registrations in Brazil, 1990–2015



Note: Data from União da Indústria de Cana-de-Açúcar (2022).

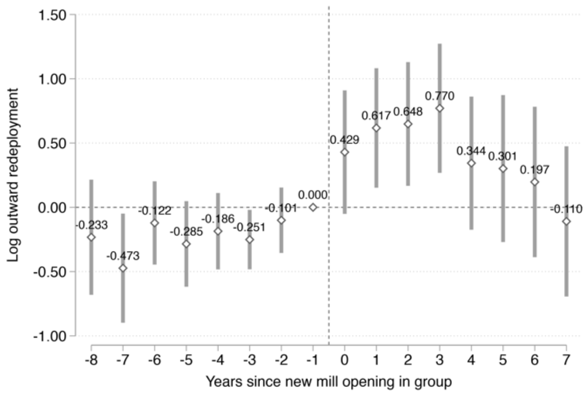
(b) Sugarcane and fuel ethanol production in Brazil, 1990–2015

Figure 3. Flex-fuel vehicles and fuel ethanol production in Brazil, 1990–2015

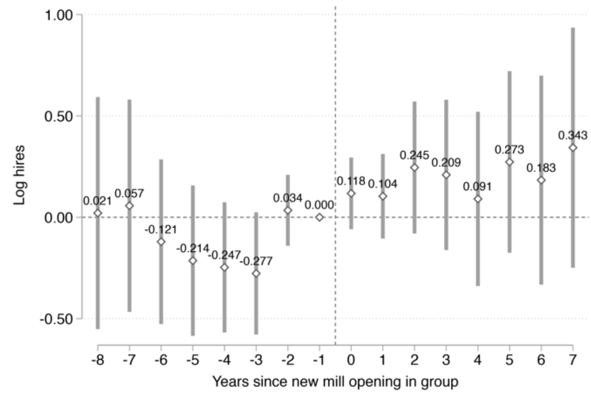


Note: Authors' calculations using data from RAIS and FAO (GAEZ).

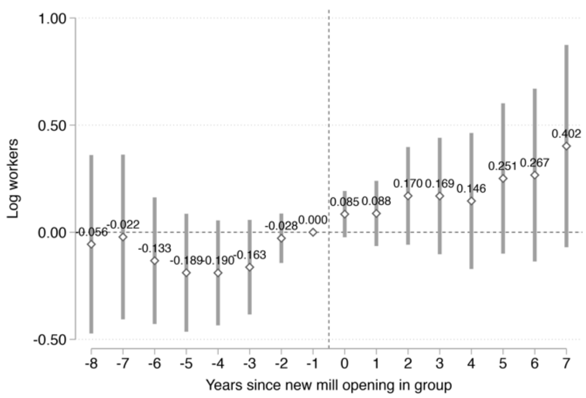
Figure 4. Sugar mill locations and land quality



(a) Outward redeployment in incumbent mills after new mill opening



(b) Hiring in incumbent mills after new mill opening



(c) Employment in incumbent mills after new mill opening

Notes: Graphs plot estimates of outward redeployment, hiring, or employment (logged and adding 1 to zeros) 8 years before and after a new mill opening (relative to the year before opening and relative to incumbent mills in business groups that did not open a mill). Estimates come from regressions that compare incumbent mills in business groups that opened a new mill and incumbent mills in business groups that did not open a new mill. We focus on business groups that opened exactly one mill. We use coarsened exact matching weights (based on employment size in 2000) in these regressions and include fixed effects for mill and year. Bands indicate 95 percent confidence intervals constructed from standard errors clustered at the mill level.

Figure 5. Outward redeployment in incumbent mills after new mill opening

ONLINE APPENDIX

Resource Redeployment as an Entry Advantage in Resource-Poor Settings

A WAGE DETERMINATION IN THE MODEL

This appendix provides further details about the model's assumptions regarding wages. As explained in the text, we assume firms are restricted to offering workers a fixed wage, w, that does not depend on output. This is the dominant type of employment contract offered in Brazil. Additionally, high- and low-skill workers must be offered the same wage because they cannot be distinguished ex-ante (Mas-Colell, Whinston, and Green, 1995).

One view of wage determination consistent with our model and empirical context is that workers in market m have an outside option, $h_m \geq 0$, and receive take-it-or-leave-it wage offers from a small number of firms that each need a limited number of workers. In Mas-Colell *et al.* (1995), h_m represents the value of home production. Similarly, in our agricultural setting, h_m could represent the value of independent farming or the wage offered in an industry other than sugar cultivation and refining, such as citrus farming. Firms entering the market observe h_m and can thus offer a wage, $w_m = h_m$, that leaves workers indifferent between employment in the sugar industry and independent farming, in which case we assume workers choose employment in the sugar industry. Wages thus vary across markets due to differences in workers' outside options. In our setting, it is natural to assume that workers' outside options in Brazil's rural frontier regions are no better than those in more established markets, which is consistent with our assumption in the text that wages in the frontier are less than or equal to wages in the initial market ($w_N \leq w_I$).

Another view of wage determination consistent with our model is that firms possess a constant-returns-to-scale technology and engage in Bertrand competition for workers following entry. When more than one firm enters a market, all workers will choose to work for the firm offering the higher wage and firms will compete away all profits, offering workers:

$$w_m = p_m \left[\lambda_m f_H(z_m) + (1 - \lambda_m) f_L(z_m)\right] \tag{A.1}$$

Given $F_m > 0$, this outcome results in a net loss. With positive fixed costs of entry, only one firm enters each market and offers workers the lowest wage they will accept, which is $w_m = h_m$. In this case, the prospect of intense competition for workers reduces firms' appetite for entry and results in monopsony (Mas-Colell *et al.*, 1995).[1] This outcome is consistent with our empirical context; of 367 municipalities with sugar mills in Brazil, only 65 have more than a single mill.

B ENTRY CONDITIONS

In this appendix, we discuss firms' market entry decisions. Throughout the main text, we assume for expositional convenience that firms operate for all periods in the initial market and that incumbents enter the frontier at $t = 3$. Alternative models of market entry and redeployment (Belenzon, Bennett, and Patacconi, 2019; Lieberman, Lee, and Folta, 2017; Santamaria, 2021) emphasize the exercise of redeployment options when exiting, whereas we examine the use of redeployment upon entry. To provide adequate space for this discussion, we omit analyses of the exit decision from our main text. Here, however, we provide sufficient conditions to support our assumptions about entry in the main text and analyze the entry decision.

[1] Mas-Colell *et al.* (1995) demonstrate this in the context of Bertrand competition in the product market, but the same is true of competition for workers in the labor market.

Entry and Exit in the Initial Market

We consider entry and exit in the initial market using backwards induction, starting from the firm's decision after $t = 2$ (after observing output and worker skill) to either exit, retain its existing worker, or replace the worker with a new hire. As explained in the main text, a firm will never replace a high-skill worker because this is the best possible outcome. Thus, the firm's choice in this situation is between exit and retaining its existing worker for another period. The firm will exit the initial market only if $p_I f_H(z_I) - w_I < 0$. If this holds, however, then the firm will never enter the initial market at $t = 1$ because the best possible payoff would be:

$$p_I f_H(z_I) - w_I - F < 0 \quad \text{(B.1)}$$

Conversely, a firm will never retain a low-skill worker and therefore must decide between exit and replacing the worker after $t = 2$. A firm that initially hires a low-skill worker will exit if:

$$p_I[\lambda_I f_H(z_I) + (1 - \lambda_I) f_L(z_I)] - w_I < 0 \quad \text{(B.2)}$$

A natural sufficient condition that justifies excluding this scenario from consideration in the main text, and that is consistent with the model of wage determination described in Appendix A, is:

$$p_m\, f_L(z_m) - w_m \geq 0 \;\; \forall\, m \quad \text{(B.3)}$$

Because wages in our model are equal to the value of home production (see Appendix A), this assumption says that market production is always at least as productive as home production for low skill workers. Furthermore, together with Assumption (1) in the main text, this implies that high skill workers are always more productive in market production. Under this condition, output in Equation (B.2) is a convex combination of quantities greater than w_I and thus the inequality in

Equation (B.2) is always satisfied. This justifies considering only firms' decisions with respect to replacing, retaining, or redeploying the worker in the main text.

Having eliminated exit from consideration via the assumption in Equation (B.3), we now show there always exists some $F_I > 0$ that justifies entry into the initial market—an assumption we make in the main text when introducing Equation (1). The total expected profit over two periods of production in the initial market is:

$$\underbrace{2\lambda_I p_I f_H(z_I)}_{\substack{Two\ high\ skill\\ workers}} + \underbrace{\lambda_I(1-\lambda_I)p_I[f_H(z_I)+f_L(z_I)]}_{\substack{One\ high\ skill\ and\ one\ low\ skill\\ worker}} + \underbrace{2(1-\lambda_I)^2 p_I f_L(z_I)}_{\substack{Two\ low\ skill\\ workers}} - \underbrace{(2w_I + F_I)}_{\substack{Two-period\\ costs}} \tag{B.4}$$

By Equation (B.3), the minimum value of this expression occurs when $p_I f_L(z_I) = w_I$. Substituting this into Equation (B.4) gives the following inequality for entry into the initial market:

$$\lambda_I(3-\lambda_I)(p_I f_H(z_I) - w_I) \geq F_I \tag{B.5}$$

The left side equals the "rent" from having a high-skill worker multiplied by the ex-ante expected number of periods the firm will produce with that worker. This is strictly positive given Assumption (1) and $\lambda_I \in (0,1)$; hence, there is always some $F_I > 0$ for which entry is preferred.

Entry in the Frontier Market

Having shown entry into the initial market is feasible and that an incumbent firm will not exit after $t = 2$ given the assumption in Equation (B.3), we now discuss entry into the frontier. (We do not consider exit from the frontier because the model ends following production in $t = 3$.) In the main text, we claim that using redeployment to overcome resource scarcity sometimes allows firms to enter markets that *de novo* firms cannot—i.e., there are markets that are ex-ante economically unattractive but that redeployment capabilities make ex-post profitable. For this to be true, the following two inequalities must hold for at least some parameters:

$$p_N f_H(z_N) - p_I(1-\lambda_I)[f_H(z_I) - f_L(z_I)] - w_I - R \geq F_N \tag{B.1}$$

$$p_N[\lambda_N f_H(z_N) + (1-\lambda_N) f_L(z_N)] - w_N < F_N \tag{B.2}$$

Equation (B.1) is the condition for entry via redeployment to be profitable, which depends both on revenue in the frontier market as well as the expected loss in revenue in the initial market (the opportunity cost of withdrawing and replacing the high-skill worker). Equation (B.2) is the condition for entry via local hiring to be profitable, which depends solely on expected profit in the frontier market. While there are several combinations of parameters under which both inequalities hold, we highlight that greater thickness in the initial market ($\lambda_I \rightarrow 1$) and lower thickness in the frontier market ($\lambda_N \rightarrow 0$) increases the gap in profits between firms entering via redeployment and those choosing to hire in external markets.

C PRICES AND REDEPLOYMENT

Here, we demonstrate how output prices in initial and frontier markets affect firms' redeployment decisions. Changes in demand conditions are the dominant inducement for redeployment in the corporate strategy literature (Anand and Singh, 1997; Dickler and Folta, 2020; Giarratana and Santaló, 2020; Wu, 2013). Our condition for redeployment—Equation (3) in the text—is given by:

$$\begin{gathered} p_2(1-\lambda_2)g(z_2) - p_1(1-\lambda_1)g(z_2) > w_1 - w_2 + R \\ \text{where } g(z) = F_H(z) - F_L(z) \end{gathered} \tag{C.1}$$

Differentiating Equation (C.1) with respect to prices in the frontier and initial markets gives:

$$\frac{\partial}{\partial p_2} = (1 - \lambda_2) g(z_2) > 0 \text{ and } \frac{\partial}{\partial p_1} = -(1 - \lambda_1) g(z_1) < 0 \quad \text{(C.2)}$$

Because $g(z) > 0 \; \forall z$, price increases in the frontier (initial market) will increase (decrease) the net benefit of redeployment. This pattern is consistent with the literature on redeployment, which emphasizes how the ability to reallocate resources between businesses allows firms to expand in attractive markets and retrench in less attractive markets (Chang and Matsumoto, 2021; Dickler and Folta, 2020; Wu, 2013).

The more novel feature of our model, however, is that output prices moderate the relationship between labor market thickness and redeployment. This follows from the second derivatives of Equation (C.2) with respect to thickness:

$$\frac{\partial}{\partial p_2 \partial \lambda_2} = -g(z_2) < 0 \text{ and } \frac{\partial}{\partial p_1 \partial \lambda_1} = g(z_1) > 0 \quad \text{(C.3)}$$

Equation (C.3) shows there are interactions between demand-side and supply-side conditions in redeployment decisions. Consistent with the theory that "internal resource redeployment only creates value if it is more efficient than external resource acquisition for the same purpose" (Folta, Helfat, and Karim, 2016), redeployment in response to price changes is more valuable in our model when markets are imperfect. The importance of price changes in the frontier and initial markets for redeployment declines as thickness of the labor markets increases. Although we do not emphasize these patterns in our empirical setting, interactions between demand- and supply-side factors are potentially a promising direction for future research.

D WAGES AND REDEPLOYMENT

This section sheds light on the incentives and outcomes for redeployed workers. While Table 11 in the main text shows that redeployed workers have higher wages than workers hired in external labor markets (in the hiring year), it is unclear whether workers benefit from redeployment. We offer a more detailed analysis of redeployment outcomes for workers by examining the wages of redeployed workers relative to the wages of a cohort of workers in the same occupation, education level, and age profile that join the same business group in the same state and year. We then follow the wage trajectories of redeployed workers and their cohorts before and after the redeployment episode. In Figure A, we plot the mean wage for redeployed workers, the mean wage for cohort workers, and the wage premium (the difference between wages of redeployed and cohort workers) over time. Wages for redeployed workers and cohort workers are similar upon joining the business group and follow a similar upward trajectory leading up to redeployment. The wages of redeployed workers increase sharply after redeployment. The wage premium soars upon redeployment and increases for several years post-redeployment. These findings show that workers tend to benefit from redeployment. The steep increase in wages post-redeployment suggests that redeployment is a good career opportunity.

E ALTERNATIVE EXPLANATIONS

Here, we present results of analyses designed to assess the explanatory power of alternative explanations for our main results. These analyses are summarized in Section 6.2 of the main text.

Retrenchment of Troubled and Failing Businesses

In Table A we present results from the difference-in-differences model examining outward redeployment, hiring, and employment levels in incumbent mills around the time their business groups open a new mill. Together with Figure 5 in the main text, these results show that while incumbent mills redeploy out more workers after opening a new mill, they do not reduce hiring or overall employment. Furthermore, the wage growth of redeployed workers discussed in Appendix D is not consistent with firms using redeployment to downsize. We conclude that redeployment in our context is not used for retrenchment purposes.

Temporary Redeployment

Redeployment is not a temporary phenomenon. One alternative explanation for our results is that firms temporarily move workers to jumpstart new businesses and train recently hired workers rather than as a substitute for local hiring. We find, however, that redeployed workers are usually not redeployed back to their original establishment and that redeployed workers stay longer in their job. Figure B show Kaplan-Meier estimates of the survival function for redeployed and non-redeployed workers—adjusting for mill dummy variables, starting year, and occupation group—where "survival" is defined as a worker remaining in their initial job with a sugar mill. This analysis demonstrates that temporary job assignments do not account for our findings.

F ALTERNATIVE LABOR MARKET MEASURES

To check that our results do not depend on a specific measure of labor market thickness, we repeat our main analyses using alternative measures (Table B). Our first alternative measure is the share of a municipality's workers employed in sugar cultivation, refining, or milling in the year 2000:

$$\lambda_m^{(1)} = \frac{E_{sm}}{E_{\cdot m}} \quad \text{(F.1)}$$

This measure is equivalent to a version of Equation (9) that sets similarity to 0 for all non-sugar industries and to 1 for the sugar industry itself. A potential disadvantage of this measure relative to our main measure is that it excludes workers who were not engaged in sugar production in 2000 but nevertheless possess related skills—for example, workers experienced with other forms of agricultural production like citrus growing and cattle ranching.

Our second alternative measure is equivalent the main measure in Equation (9) but uses a rescaled Euclidean distance rather than cosine similarity to measure industry similarity:

$$\lambda_m^{(2)} = \frac{1}{E_{\cdot m}} \sum_{j=1}^{J} S_j E_{jm} \text{, where } S_j = 1 - \frac{d_j}{\max\{d_1, d_2, \dots, d_J\}} \text{ and } d_j = \left\| v_j - v_s \right\|_2 \quad \text{(F.2)}$$

The Euclidean distance is used as a measure of industry relatedness in several studies of redeployment (Sakhartov and Folta, 2014, 2015).

Our third alternative variable relies on a measure of industry relatedness constructed from labor flows between industries (Neffke and Henning, 2013; Neffke, Otto, and Weyh, 2017). The intuition behind this measure is that if workers frequently move between industry j and k, then the two industries likely have similar human capital requirements. To construct this measure, we calculate the ratio of labor flows to "expected flows" between each industry and sugar cultivation, milling, and refining. As in Neffke and Henning (2013), we define "expected flows" as flows predicted from a regression of observed flows on industry employment sizes, their interaction, and a year fixed effect. Specifically, we use a Poisson model for the observed number of job transitions between industries j and k in year t:

$$E\left[F_{jkt} \middle| E_j, E_k\right] = \exp\left(\alpha \log(E_j) + \beta \log(E_k) + \gamma \log(E_j) \log(E_k) + \tau_t\right) \qquad \text{(F.3)}$$

and use the estimated coefficients to calculate expected flows, $\hat{F}_{jkt}$. To prevent our sample firms from affecting the measure, we estimate Equation (F.3) and base all relatedness calculations on data from 1998–2002, which predates our sample period of new mills.[2] The similarity between industry j and sugar production is then $S_j^F = \frac{1}{T}\sum_{t=1}^{T} F_{jst}/\hat{F}_{jst}$, which takes values greater than 1 for industries that are related (i.e., actual flows exceed expected flows based on industry size alone) and takes values between 0 and 1 for industries that are unrelated. As with the Euclidean distance, we rescale the measure to be between 0 and 1 and use the scaled measure to calculate a weighted average of employment in each municipality.

$$\lambda_m^{(3)} = \frac{1}{E_{\cdot m}} \sum_{j=1}^{J} \tilde{S}_j^F E_{jm}\text{, where } \tilde{S}_j^F = \frac{S_j^F - \min\{S_1^F, S_2^F, \dots, S_J^F\}}{\max\{S_1^F, S_2^F, \dots, S_J^F\} - \min\{S_1^F, S_2^F, \dots, S_J^F\}} \qquad \text{(F.4)}$$

A potential advantage of this measure is that it captures asymmetries in human capital flows between two industries; S_{jk}^F does not necessarily equal S_{kj}^F. A potential disadvantage of this measure in our context is that it relies on observing flows from other industries into sugar production before the boom in sugar demand that comprises our sample period. Unlike the distance in occupational profiles we use in the main text, the flow-based measure cannot capture the *potential* for workers in industry j to shift into sugar production absent a prior propensity to do so.

[2] Using several years of flows and averaging reduces potential measurement error (Neffke, Otto, and Weyh, 2017). The correlation in S_{jt}^F across consecutive years is 0.58, which resembles Neffke *et al.*'s (2017) finding using German data that "in two consecutive years, correlations barely exceed the 0.5 mark."

G ALTERNATIVE LABOR MARKET DEFINITIONS

We consider the sensitivity of the findings to different geographical definitions of labor markets. Table C shows the results of re-estimating our primary models after re-defining labor markets as all municipalities within 20 or 50 km of a sugar mill. Columns 1–2 reproduce results from Table 5 for reference while columns 3–6 use the alternative definitions. When using a 20 km radius to define labor markets, we find a negative but weaker relationship between redeployment share and thickness. When using a 50 km radius, we find no statistically significant relationship. This pattern of attenuation is consistent with the fact that sugar activity is concentrated in close proximity to mills (Sant'Anna *et al.*, 2016). Additionally, it suggests that unobserved regional factors correlated with thickness do not drive our results.

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TABLES

Table A. Incumbent mills before and after a new mill opening

	(1)	(2)	(3)
	Log outward redeployment	Log hires	Log workers
Treated × Post-opening	0.614	0.278	0.276
	(0.218)	(0.217)	(0.182)
Mill fixed effect	●	●	●
Year fixed effect	●	●	●
Observations	2,088	2,088	2,088
R^2	0.582	0.655	0.592

Notes: Table shows difference-in-differences estimates of log outward redeployment, log hires, and log workers in incumbent business group mills after a new mill opening. These estimates come from regressions that compare incumbent mills in business groups that opened a new mill and incumbent mills in business groups that did not open a new mill. We use coarsened exact matching weights (based on employment size in 2000) in these regressions. We focus on business groups that opened exactly one mill between 2001 and 2014. Regressions include mill and year fixed effects. Robust standard errors clustered at the mill level in parentheses.

Table B. Alternative measures of labor market thickness

DV = Redeployment share	(1)	(2)	(3)	(4)	(5)	(6)
Thickness in frontier (λ_2)	-0.113	-0.212	-0.213	-0.467	-0.200	-0.329
	(0.038)	(0.074)	(0.093)	(0.154)	(0.080)	(0.101)
Thickness in initial market (λ_1)	0.128	0.123	0.062	0.111	0.087	0.138
	(0.060)	(0.078)	(0.041)	(0.062)	(0.051)	(0.073)
Wages in frontier (w_2)		0.010		0.043		0.038
		(0.059)		(0.060)		(0.055)
Wages in initial market (w_1)		0.038		0.026		0.005
		(0.067)		(0.067)		(0.065)
Land quality in frontier (z_2)		0.151		0.136		0.103
		(0.105)		(0.096)		(0.090)
Land quality in initial market (z_1)		-0.304		-0.411		-0.291
		(0.234)		(0.275)		(0.253)
Control variables		●		●		●
Opening year fixed effect		●		●		●
Observations	91	91	91	91	91	91
R^2	0.063	0.276	0.039	0.290	0.072	0.328

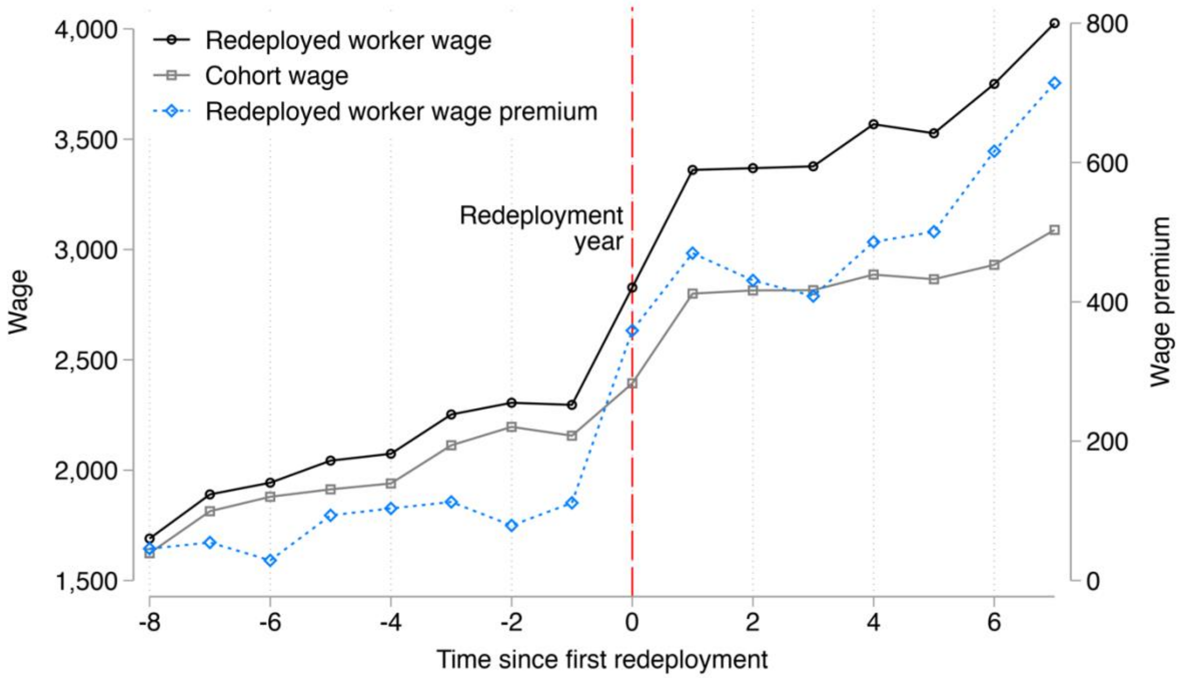
Notes: The dependent variable is the share of workers hired via redeployment (over all workers hired in the mill). Thickness in Columns (1) and (2) is defined as the share of workers in the sugar industry. Thickness in Columns (3) and (4) is calculated using the L2 Euclidean distance measure. Thickness in Columns (5) and (6) is calculated using the empirical flow of workers across industries. Columns (2), (4), and (6) include controls (log population, log area, unemployment rate) for both the origin and destination municipality and mill opening year fixed effects. Sample is limited to 91 mills that belonged to business groups and were inaugurated after 2000. Robust standard errors in parentheses.

Table C. Alternative labor market definitions

DV = Redeployment share	(1)	(2)	(3)	(4)	(5)	(6)
Thickness in frontier	-0.114	-0.248				
	(0.050)	(0.087)				
Thickness within 20 km			-0.102	-0.211		
			(0.053)	(0.088)		
Thickness within 50 km					0.084	0.076
					(0.109)	(0.138)
Control variables		●		●		●
Opening year fixed effect		●		●		●
Observations	91	91	91	91	91	91
R^2	0.023	0.271	0.018	0.254	0.006	0.198

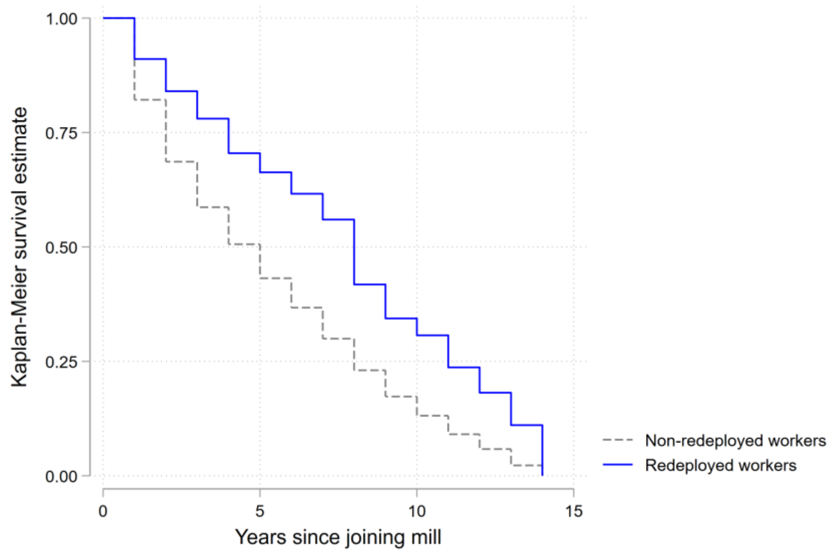
Notes: The dependent variable is the share of workers hired via redeployment (over all workers hired in the mill). Columns (2), (4), and (6) include controls (log median wage, log land quality, log population, log area, unemployment rate) for both the origin and destination municipality and mill opening year fixed effects. Sample is limited to 91 mills that belonged to business groups and were inaugurated after 2000. Robust standard errors in parentheses.

FIGURES



Notes: Graph plots the mean wage for redeployed workers, the mean wage for cohort workers, and the wage premium (the difference between wages of redeployed and cohort workers) by years since redeployment. Cohort is defined as a group of workers in the same occupation, education level, and age profile that enter the same business group in the same state and year. We limit the sample to redeployed workers before and after the first redeployment episode (excluding subsequent episodes) and cohort workers in cohorts that have at least one redeployed worker.

Figure A. Wage trajectories of redeployed workers and their cohorts



Notes: Figure shows covariate-adjusted survivor functions for redeployed and non-redeployed workers in new business group mills. The survivor function is adjusted by the inclusion of dummies for mill, starting year, and occupational group. The sample is limited to individual workers' first employment spell in the mill.

Figure B. Survivor function for redeployed and non-redeployed workers