The Impact of Bank Credit on Labor Reallocation and Aggregate Industry Productivity

John Bai, Daniel Carvalho and Gordon Phillips*

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Using a difference-in-difference methodology, we find that the state-level banking deregulation of local U.S. credit markets leads to significant increases in the reallocation of labor within local industries towards firms with higher marginal products of labor. Using firm production functions estimated with plant-level data, we propose and examine an approach that quantifies the industry productivity gains from labor reallocation and find that these gains are economically important. Our analysis suggests that labor reallocation is a significant channel through which credit market conditions affect the aggregate productivity and performance of local industries.

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* We thank seminar participants at the University of Southern California. Authors are from the University of Southern California. Carvalho can be reached at dcarvalho@marshall.usc.edu, Bai can be reached at jbai@marshall.usc.edu, Phillips can be reached at gordonph@marshall.usc.edu .

An important question in economics and finance is to understand how financial markets affect real economic activity. Given the role of financial markets in moving resources towards the best economic opportunities, previous research has focused on how financing frictions may impact the allocation of resources and, as a consequence, aggregate productivity. Two main channels have been posed and debated.[1] Namely, financing frictions can lower aggregate productivity by leading to a misallocation of capital across existing firms or by distorting firms' entry and exit decisions. Despite the central importance of labor as a production factor, limited attention has been paid to the role of financing markets in facilitating the reallocation of labor towards the most productive firms. Indeed, existing research typically assumes that financing frictions do not directly affect firms' ability to adjust their labor decisions, and that these frictions influence the allocation of labor only indirectly through their impact on the allocation of capital. According to this view, financial markets will not have a first-order effect on aggregate productivity by facilitating the reallocation of labor towards the most productive firms.[2]

In this paper, we study the role of financial markets in influencing aggregate productivity by shaping the reallocation of labor across firms. Using a difference-in-difference analysis, we examine how reforms in U.S. local credit markets through major state-level banking deregulations affect the aggregate productivity of local industries by shaping the reallocation of labor across firms. We find that these state-level banking deregulation events are associated with significant increases in the within industry reallocation of labor towards higher marginal product of labor firms and that labor reallocation is associated with large gains in aggregate industry productivity.

Intuitively, labor reallocation will only affect the aggregate productivity of an industry to the extent that these reallocations are correlated with differences in firms' marginal products of labor. We propose and estimate an approach to formalize this intuition and measure the overall impact of within-industry labor reallocations on industry productivity growth, which we label labor reallocation gains. We build on previous research suggesting how to use plant-level data to decompose aggregate industry productivity growth into its different determinants and isolate the contribution of labor reallocation to this growth.

[1] Recent examples include Hsieh and Klenow (2009), Bartelsman, Haltiwanger, and Scarpeta (2013), Buera, Kaboski, and Shin (2011), Collard-Wexler and De Loecker (2014) and Midrigan and Xu (2014).
[2] If financing frictions are not preventing labor to move across firms with diverging returns in using labor, there is no reason to expect financing frictions to have first-order effects on aggregate productivity through labor misallocation.

We argue that financing frictions can potentially have significant effects on aggregate productivity by directly affecting labor reallocations. First, there are different reasons to expect financing frictions to directly affect firms' employment decisions. To begin, firms will need financing to employ more labor if there is a timing delay between payments to workers and the additional cash flows generated by the use of more labor. Firms also often face training and hiring costs, and firm-specific investments by workers can be important, so expanding labor often requires upfront costs.[3] Unlike physical capital which can serve as collateral, it can be harder for labor intensive firms to provide as much collateral to banks as capital intensive firms can provide. Capital also has an additional financing advantage over labor as physical capital is frequently leased directly from capital providers.

Financially constrained firms can also expose workers to greater labor income risks and workers might factor this issue into account when choosing among potential employers.[4] Since firms with higher returns in expanding their labor are likely to be the ones with greater employment growth in the absence of financing frictions, these frictions can limit the extent to which labor is reallocated towards firms with the highest returns in using labor and, as a consequence, lower aggregate productivity. Even if financing constraints in expanding labor were smaller than the ones involved in the financing of long-term capital, their impact on aggregate productivity could still be important when compared to the impact of financing frictions on aggregate productivity through the misallocation of capital, as labor is a significantly larger share of production relative to capital.

General equilibrium effects are also potentially important for labor. As more productive firms expand and drive up factor prices, they trigger greater reallocation by crowding out less productive firms (e.g. Melitz (2003)). To the extent that the aggregate supply of labor is more inelastic than the one of capital, these effects will be more important in labor markets. Similarly, frictions in redeploying factors across firms could be less important for labor. Therefore, whether financing frictions can have an economically significant impact on aggregate productivity by constraining the reallocation of labor is ultimately an empirical question.

[3] Even if some of these returns are generated over short-term horizons, Paravisini et al. (2014) suggests that firms can face significant financing frictions in raising short-term working capital.

[4] Agrawal and Matsa (2013) and Brown and Matsa (2013) provide evidence supporting this idea.

We focus on the within-industry resource allocation.[5] Reallocation of labor is defined in broad terms to include any change in the shares of labor allocated to different firms in an industry. These changes in labor shares will incorporate both direct reallocations of labor across firms, where workers switch firms, but also the differential employment growth rates of firms within an industry. Labor reallocation gains are then the component of industry productivity growth that can be explained by changes in the labor shares of firms over time.

Our approach allows us to quantify the impact that these major state-level credit market reforms have on the aggregate output of local industries through the labor reallocation channel. By considering different decompositions of industry productivity growth, our approach also allows us to compare the economic importance of this effect to alternative channels through which credit markets can affect the aggregate productivity and performance of local industries. Credit markets can affect the aggregate productivity growth of local industries through changes in the reallocation of capital, changes in firm-level productivity growth, or changes in the entry and exit decisions of firms. Finally, in addition to changes in the reallocation of labor, credit markets can affect the performance of local industries by allowing them to expand their aggregate labor.

We implement this analysis with plant-level data from the U.S. Census Bureau on a broad sample of small U.S. manufacturing firms. The essential requirements for the implementation of our approach are measuring within industry gaps in firms' marginal products and empirically isolate the impact of credit market reforms. In order to measure differences in firms' marginal products, we build on previous research in empirical industrial organization which explicitly addresses the simultaneity and selection biases involved in the estimation of production functions (Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2006)).

We examine the within industry reallocation of labor and the magnitude of industry productivity changes after state-level deregulation in credit markets, when compared to industries in states that did not deregulate credit markets around the same time. The state-level deregulations that we study allowed banks to operate across state borders, as well as reduced local bank monopolies. During our sample period, small U.S. firms heavily relied on loans from local banks as a source of external financing (e.g., Petersen and Rajan (1994)). Previous research has suggested

[5] Our approach follows Olley and Pakes (1996) and Hsieh and Klenow (2009). This focus on the within industry allocation of resources is often motivated by the existence of significant and persistent gaps in productivity within industries (Bartelsman, Haltiwanger, and Scarpeta (2013)).

that these reforms affected local credit markets, leading to higher local economic growth and mattered especially for small local firms (e.g., Jayaratne and Strahan (1996), and Cetorelli and Strahan (2006)). These state-level deregulations have the advantage that they are staggered across states over time. Kroszner and Strahan (1999, hereafter KS) provide evidence suggesting that these differences in timing across states were not related to contemporaneous changes in state-level economic or banking conditions.[6]

We estimate that this state banking deregulation is associated with economically important increases in labor reallocation gains. Across different deregulation episodes and specifications, these increases represent between 20%-45% additional increases in productivity over time relative to pre-deregulation changes in productivity. We show that our results are robust to examining geographically close markets that span multiple geographically close states that experience different timing of state banking deregulation. By examining how credit market reforms affects a specific component of aggregate industry productivity growth, labor reallocation gains, we isolate how important shifts in credit conditions matter for aggregate industry productivity through the labor reallocation channel.

We then quantify how these additional reallocation gains associated with credit market deregulation affect the level of industry output and productivity. The scope for such effects is arguably more limited in the U.S. relative to many other countries in which resource misallocation has been studied. We therefore evaluate these previous magnitudes not only on the average local industry in our sample, but also in subsamples where the scope for such gains is predicted to be larger. We predict such gains using data prior to deregulation and measures of potential reallocation gains using our framework. Intuitively, industries with high potential gains are industries with higher dispersion of marginal products prior to deregulation. We find that these changes in labor reallocation lead to economically large increases in industry productivity especially in industries with high dispersion of marginal products.

We find that these results are robust to several checks on the two essential requirements of our analysis. First, we address a potential concern regarding the accuracy of our measured marginal

[6] Kroszner and Strahan (1999) argue that these reforms were triggered by national-level technological changes, which weakened local banking monopolies and reduced their incentives to fight against deregulation, and that differences in the timing of deregulation across states largely capture long-term state characteristics predicting the response of interest groups to these national-level changes.

product of labor differences across firms. We find that our results are robust across a wide range of specifications and approaches to estimating production functions, including evidence that our results are not driven by omitted differences in worker skill across firms. Second, we address a concern with the identification of the effect of local banking deregulation. In our basic findings, identification comes from the staggered nature of deregulation episodes across states.

Our identification hinges on the assumption that state-level banking deregulation is not related to other changes differentially affecting the growth of higher marginal product firms within local industries. We provide direct evidence that deregulation is not correlated with prior changes in this differential growth. We then examine these findings in depth by constructing a sample of geographically and economically closely matched industries. For each local industry in a state that deregulated credit markets during our sample (treated industry), we construct a group of control industries which include only geographically close industries located in states that did not deregulate credit markets around the same period. We find that, relative to matched control industries, treated industries significantly increase their resource reallocation towards higher marginal product firms in the years immediately after their deregulation episodes. Moreover, we find that the magnitudes of these effects match the ones from our basic results.

We also consider the impact of credit market deregulation on industry productivity through the alternative channels previously discussed. We find that labor reallocation gains are important when compared to the productivity gains associated with capital reallocations and these alternative channels. Consistent with prior research, we find that credit market deregulation is associated with increases in firm-level productivity (Krishnan, Nandi and Puri (2014)). For the average industry, we find that the magnitude of the previous firm-level productivity effect is comparable to the ones of the reallocation of production factors, but economically smaller. Moreover, in industries more likely to have misallocation, the magnitude of the labor reallocation channel is significantly larger than the firm-level channel documented by Krishnan, Nandi and Puri. These results suggests the importance of studying the implications of financing frictions for productivity at the industry level and the importance of labor reallocations in driving this gap.

While we find evidence that firms' entry and exit decisions change with deregulation, our analysis suggests that the implications of these effects for industry productivity are limited when compared to the intensive margin effects we document. In the context of the U.S. banking deregulation experience, these findings support the view that changes in credit markets affect industry productivity more by improving the resource allocation of firms at later stages of their life instead of improving selection of more productive firms at birth. This is consistent with Kerr and Nanda (2009) who show that it is hard to predict the hard to predict the quality of new firms before they start operating and producing results.

Overall, our paper makes two main contributions to a growing literature on the impact of finance on resource allocation and aggregate productivity, which we discuss in greater detail in the next section. First, we provide evidence that the labor reallocation channel can be an economically important channel through which financial markets affect aggregate productivity. Second, we provide direct evidence that changes in financial markets can have economically important effects on aggregate productivity through their impact on the intensive margin allocation of resources. Finally, our results suggest that such effects can be significant even in the context of the U.S.

These findings have different broad implications. They suggest that financing frictions directly affect firms' labor decisions and that incorporating such effects can be important for understanding their real effects.[7] They also provide new evidence on the specific mechanisms through which important reforms in credit markets can matter for the real economy and relate to previous research on financial development and growth. While this literature has emphasized that financial markets matter for economic growth, the specific mechanisms driving this effect is still a topic of open debate.[8] Finally, they provide new evidence on the determinants of differences in aggregate productivity across economies. A growing body of research has emphasized that differences in the within-industry allocation of resources play a significant role in explaining aggregate productivity gaps at the industry or country level, but has not converged on the underlying mechanisms driving these differences in resource allocation nor whether these productivity gaps may be mitigated by improvements in credit markets.[9]

[7] Previous research has examined the impact of financing frictions on firm employment and aggregate unemployment (Benmelech et al. (2011) and Chodorow-Reich (2014)), as well as dispersions in employment growth rates across industries (Pagano and Pica (2012)), but has not on examined the effect on firm and aggregate industry productivity.
[8] For example, see Levine (1997), Rajan and Zingales (1998), Beck, Levine, and Loayza (2000) and the references therein for the effect of financial development on growth.
[9] For example, see Olley and Pakes (1996), Hsieh and Klenow (2009), Bartelsman, Haltiwanger, and Scarpeta (2013), and Collard-Wexler and De Loecker (2014).

1. Related Literature

In this section we discuss in greater detail the connection between our paper and previous research on how financial markets affect the allocation of resources and aggregate productivity. Previous research has estimated calibrated models with financing frictions and used them to quantify the channels through these frictions affect aggregate productivity (Buera, Kaboski, and Shin (2011), Midrigan and Xu (2014), and the references therein). A first way that the analysis in this paper complements these papers is by considering the role of the labor reallocation channel. We provide evidence on how differences in financial markets affect the reallocation of resources and aggregate productivity conditional on the importance of other factors. In practice, there is a range of frictions potentially distorting the allocation of resources within an industry, such as labor and product market regulations, and political institutions. For tractability, calibrated exercises typically assume these frictions are not present and attribute all deviations from benchmarks in resource allocation to financing frictions.[10] A final way that our analysis complements these exercises is providing direct evidence on how significant changes in credit markets affect the different determinants of industry productivity growth.

Other papers have also connected credit markets reforms or measures of financial development to differences in resource allocation within and across industries. Wurgler (2000) relates cross-country differences in financial development to a measure of how efficiently countries allocate capital across their industries. Bertrand, Schoar, and Thesmar (2007) analyze how French banking deregulation reforms affect the entry and exit decisions of firms and the link between their product market shares and operating performance. Cetorelli and Strahan (2006) and Nanda and Kerr (2009) study how U.S. state-level banking deregulations affect the size distribution of firms and their entry and exit decisions, respectively. While the effects documented in this previous research are likely to have implications for aggregate productivity, these implications are not explicitly analyzed. In the absence of such analysis, the quantitative implications of these results for the different channels through which financial markets affect aggregate productivity are unclear. More

[10] While we do not have a calibrated model, Moll (2014) emphasizes that tractability issues limit researchers' ability to evaluate the robustness of such quantitative exercises to different specifications of the environment and illustrates how changes in some commonly used assumptions, such as a focus on steady-state outcomes, can have first-order effects on the results.

specifically, it is unclear from this evidence whether financial markets can have a first-order effect on aggregate productivity by affecting the reallocation of labor.

Larrain and Stumpner (2013) explicitly analyze how cross-country differences in financial development across Eastern European countries affect different components of aggregate industry productivity. They do not consider the role of financial markets in affecting aggregate industry productivity through the reallocation of labor and assume that firms' marginal products of labor are equalized to wages, what implies that such gains are equal to zero. Their analysis also does not separates the effect of financial markets on industry productivity through intensive margin reallocations from their effects through changes in the entry and exit decisions of firms in the data due both to market selection and data coverage.

1. Methodological Framework

In this section, we describe our methodology to quantify the significance of the labor reallocation channel in greater detail and then present the results implementing our methodology.

2.1 Measuring Marginal Reallocation Gains

We start by illustrating how to isolate the contribution of resource reallocation to marginal changes in industry productivity using first-order approximations for changes in industry output over time. A firm *i* in industry *j* and time *t* can produce output Y_{ijt} with a production function given by:

$$Y_{ijt} = A_{ijt}F(K_{ijt}, L_{ijt}, M_{ijt}), \quad (1)$$

where A_{ijt} is a time-variant and firm-specific productivity component, K_{ijt} is the firm's capital stock, L_{ijt} denotes the labor used in production, and M_{ijt} denotes materials. As is common in the productivity literature, productivity A_{ijt} is modelled as a Hicks-neutral term. As is also common in this literature, we define firms' output as their total revenues deflated with an industry-specific price deflator. Firm total factor productivity (TFP) is defined as A_{ijt}.

We define differences in industry productivity as differences in industries' value added given the same aggregate industry factors. Similarly, we define industry productivity growth as the industry value added growth in excess of what can be predicted by the aggregate growth of industry production factors. We focus on value added because it avoids double counting output across industries. In our main results, percentage differences in industry value added are measured at a fixed price for industries' output.[11] We are interested in analyzing how the reallocation of resources across an industry's existing firms contributes to industry productivity growth. In our initial analysis of marginal changes in industry productivity, we focus on industry productivity gains conditional on a given sample of industry firms. When we extend our current analysis to examine the contribution of resource reallocation to cumulative changes in industry productivity, we explicitly take into account the fact that this sample of firms changes over time due to entry and exit. Let I_{jt} denote a fixed set of firms that exist in industry j around time t. Our first definition of industry output is $Y_{jt} = \sum_{i \in I_{jt}} Y_{ijt}$.[12] For any production factor X_{ijt}, let $X_{jt} = \sum_{i \in I_{jt}} X_{ijt}$ denote the industry aggregate factor. Notice that, in general, the aggregation of firms' production functions will not necessarily lead to an industry production function with a separable TFP term as in (1). In general, the simple aggregation of firms' individual outputs gives us:

$$Y_{jt} = G(N_{jt}, \{A_{ijt}, SK_{ijt}, SL_{ijt}, SM_{ijt}\}, K_{jt}, L_{jt}, M_{jt}), \quad (2)$$

where $SF_{ijt} = \frac{F_{ijt}}{F_{jt}}$ is a firm's industry share of production factor F, N_{jt} is the number of firms in I_{jt}, and $\{A_{ijt}, SK_{ijt}, SL_{ijt}, SM_{ijt}\}$ denotes the joint distribution of these variables across N_{jt} observations.

The allocation of resources in this framework is defined in broad terms and captures any differences in the shares of factors allocated to different firms within an industry.[13] Changes in these shares, which we label resource reallocation, will incorporate both direct reallocations of resources across firms, such as asset sales, but also the differential growth rates of firms within an industry. By using a first-order approximation, we can isolate the importance of changes in the

[11] We will also consider measuring differences in industry productivity using simple differences in industry total sales minus material costs. Evaluating differences in output at fixed prices is common in measures of aggregate productivity (e.g., Basu and Fernald (2002), and Petrin and Levinsohn (2012)).
[12] If firms face different relative prices within an industry, this measure will not necessarily capture real industry output. We argue that if dispersion in firm-specific prices is important in a typical industry, it is likely to capture differentiated goods to a great extent. Therefore, one cannot simply sum real output across firms to construct a measure of real industry output. We will consider an alternative measure of industry output below.
[13] This broad definition of resource allocation is commonly used in studies of industry productivity growth (e.g., Olley and Pakes (1996)) and the literature linking within-industry resource allocation to aggregate productivity (e.g., Hsieh and Klenow (2009)).

allocation of resources in explaining marginal changes in industry productivity over time. More formally, industry productivity growth is defined as:

$$IPG_{jt} = \left(\frac{1}{1-sm_{jt}}\right)\left(\frac{dln(Y_{jt})}{dt} - \alpha_{jt}\frac{dln(K_{jt})}{dt} - \beta_{jt}\frac{dln(L_{jt})}{dt} - \gamma_{jt}\frac{dln(M_{jt})}{dt}\right), \tag{3}$$

where sm_{jt} is the ratio of industry material costs to industry revenue and α_{jt}, β_{jt} and γ_{jt} denote industries' capital, labor and materials' elasticity, respectively. The elasticity of each of these factors is computed using the marginal product of the aggregate factor in (2). For example, industry capital elasticity can be defined as $\alpha_{jt} = \frac{K_{jt}}{Y_{jt}}\frac{\partial Y_{jt}}{\partial K_{jt}}$. This will tell us the increase in aggregate output predicted by an increase in aggregate factors, holding constant these other determinants of aggregate output. The term $\left(\frac{1}{1-sm_{jt}}\right)$ coverts these industry output gains into value added gains measured at current industry prices. Note that $\left(\frac{1}{1-sm_{jt}}\right) = \frac{Y_{jt}}{VA_{jt}}$, where VA_{jt} is industry value added. In the simple case where the industry production function has a separable TFP term as in (1), then (3) will estimate industry productivity growth as TFP growth scaled by $\left(\frac{1}{1-sm_{jt}}\right)$.

In Appendix A we show that one can write (3) as:

$$IPG_{jt} = \left(\frac{1}{1-sm_{jt}}\right)\left(\sum_{i\in I_{jt}}\frac{Y_{ijt}}{Y_{jt}}\frac{dln(A_{ijt})}{dt} + LRG_{jt} + KRG_{jt} + MRG_{jt}\right), \tag{4}$$

where $LRG_{jt} = \frac{L_{jt}}{Y_{jt}}\sum_{i\in I_{jt}}\frac{\partial Y_{ijt}}{\partial L}\frac{dSL_{ijt}}{dt}$ denotes labor reallocation gains and the other two terms are defined analogously based on capital and materials. The first term in (4) captures the contribution of firm-level productivity growth to industry growth. The other three terms capture the contribution of resource allocation to industry productivity growth, which we label as reallocation gains. These gains capture the additional growth in industry output due to shifts in firms' factor shares. More precisely, they capture the difference between the realized marginal growth of industry output and the growth we would observe in the absence of any changes in factor shares. To illustrate the intuition for these gains, consider the case of labor reallocation gains. Since $\frac{dSL_{ijt}}{dt}$ has to add up to zero in the industry, these gains capture an industry covariance between firms' marginal products and $\frac{dSL_{ijt}}{dt}$. Intuitively, reallocation gains are positive (negative) only to the extent that higher marginal product firms grow faster (slower) within an industry.

We emphasize the different potential determinants of reallocation gains. In Appendix A we show that one can approximate LRG_{jt} as:

$$LRG_{jt} \approx \frac{Var\left(\frac{\partial Y_{ijt}}{\partial L}\right)}{E\left(\frac{\partial Y_{ijt}}{\partial L}\right)} \frac{L_{jt}}{Y_{jt}} LRSens_{jt}, \tag{5}$$

where $Var(.)$ and $E(.)$ capture variance and expected values measured using the industry distribution and $LRSens_{jt}$is the sensitivity of labor reallocation to the marginal product of labor in the industry. $LRSens_{jt}$ is the additional increase in $\frac{dlog(SL_{ijt})}{dt}$ predicted by a given percentage increase in $\frac{\partial Y_{ijt}}{\partial L}$. More formally, is the coefficient on the log of $\frac{\partial Y_{ijt}}{\partial L}$ in a linear regression of $\frac{dlog(SL_{ijt})}{dt}$ on the previous variable and a constant.[14] This sensitivity measures the extent to which industries reallocate resources in response to a given gap in the marginal product of its firms and, intuitively, captures differences in the way industries allocate resources across given opportunities.

As equation (5) illustrates, the impact of changes in $LRSens_{jt}$ on LRG_{jt} depends on the degree of dispersion in marginal products within the industry and the labor-to-output ratio in the industry. The same sensitivity of reallocation to gaps in marginal products translates into higher productivity gains when there are larger gaps in marginal products in the first place. The output gains from changing these shares are also more important when the industry relies more on the factor per unit of output. These effects are measured by $\frac{LRG_{jt}}{LRSens_{jt}}$, which captures differences in the potential industry productivity gains from reallocating resources across opportunities in a given way. We label this ratio as the potential reallocation gains.

2.2 Examining the Impact of Credit Market Reforms

We examine the impact of a significant credit market reform on our previous reallocation gains. By doing this, we can evaluate how these changes in credit markets affect industry productivity

[14] The approximation comes from the fact that we replace a regression coefficient in levels by one measured in logs adjusted based on the average value of the variables.

through their impact on previous components of industry productivity changes.[15] Moreover, we analyze this effect on the different components of marginal reallocation gains - either by reallocation gains of existing firms or other determinants of industry productivity, such as firm entry and exit decisions. This allows us to better understand how credit markets impact reallocation gains. To the extent that credit markets matter by influencing the allocation of resources across given opportunities, we should expect them to affect reallocation gains through the sensitivity of resource reallocation to marginal products. Notice that all the terms in this analysis can be measured if we have estimated the production function specified in (1).

The credit market reforms we examine are state-level banking deregulations. Prior to the 1970s most U.S. states had restrictions on banks' ability to operate within and across state borders that had remained historically stable. Given that small U.S. firms mostly relied on geographically close banks as a source of external financing until the early 1990s (Petersen and Rajan (2002)), these restrictions created local banking monopolies (Kroszner and Strahan (1999, hereafter KS)). Between the early 1970s and early 1990s states relaxed these restrictions in a staggered way. Following previous research on U.S. state banking deregulation, we focus on two main types of restrictions imposed by states. First, states imposed restrictions on intrastate branching. For example, these included restrictions on the ability of multibank holding companies to convert branches of acquired subsidiary banks into branches of a single bank, as well as restrictions on banks' ability to open new branches. As Jaraytane and Strahan (1996), and others, we choose the date of intrastate deregulation as the date in which a state permits branching through mergers and acquisitions. Second, the Douglas amendment to the Bank Holding Act of 1956 prevented a bank holding company from acquiring banks in another state unless that state explicitly permitted such acquisitions by statute. No state allowed such acquisitions until the late 1970s. States then entered reciprocal regional or national arrangements which allowed their banks to be acquired by banks in any other state in the arrangement. Except for Hawaii, all states had entered such agreements in 1993. These episodes of interstate deregulation culminated with the passage of the 1994 Riegle-Neal Interstate Banking and Branching Efficiency Act, which codified these state-level changes at the national level. As emphasized by Cetorelli and Strahan (2006), because of national-level

[15]After presenting our main analysis, we also provide some evidence on the relative importance of this channel versus other channels through which productivity can be impacted by credit markets, such as changes in firm-level productivity and firms' entry and exit decisions.

deregulation and changes in lending technology (Petersen and Rajan (2002)), it becomes increasingly less plausible to view banking markets as local after this period. Our data is available from 1976 and, motivated by the above timeline, we end our sample in 1993.

We follow Amel (1993) and Kroszner and Strahan (1999) in determining the dates of interstate and intrastate deregulation. Table 1 shows these dates and illustrates the large number of interstate deregulation episodes during our sample period. Given that previous research has provided direct evidence that these deregulation episodes are associated with changes in the borrowing terms of small local firms, e.g. reductions on interest rates, we will focus our analysis on the industry productivity consequences of these deregulation episodes.[16] We are interested in linking changes in aggregate industry productivity to overall credit market conditions faced by an industry. Therefore, the unit of analysis in our results will be an industry-state, which we label as a local industry. In our analysis, we only include small firms with a strong geographic exposure to a given state. More specifically, when defining each local industry, we include only single-plant firms. As we discuss below, these firms represent a significant portion of the aggregate sales and factors in their industry-state. Our results then analyze changes in the aggregate productivity of these local industries using our previous framework.[17]

2.3 Alternative Measures of Industry Output and Productivity

We also consider alternative measures of industry output. One important issue is that differences in firm output $Y_{ijt} = P_{ijt}Q_{ijt}$ in equation (1) can reflect differences in the physical quantity of output Q_{ijt} but also capture differences in firm-specific relative prices P_{ijt} (as emphasized by Foster, Haltiwanger and Syverson (2008)). If this dispersion in firm-specific prices is important then our previous industry output measure will not capture real industry output. We argue that if differences in relative prices are important in a typical industry, they are likely to capture differentiated goods to a great extent. Therefore, one cannot simply sum real output across firms to construct a measure of real industry output. One alternative approach to aggregate firm output into a measure of industry output is to define industry output growth as the weighted average

[16] See Krozsner and Strahan (1999), Nanda and Kerr (2009)), and the references therein for a more detailed discussion of state banking deregulation and previous research documenting its effects.

[17] One issue with this approach is that, in addition to entry and exit in an industry, firms might transition between being single-plant and a multi-plant firm. We found that these transitions are empirically limited and their implication for the aggregate productivity of local industries is limited.

growth of firm real output in the industry. More precisely, we can define industry output growth as $\frac{dln(Y_{jt})}{dt} = \sum_{i \in I_{jt}} \frac{Y_{ijt}}{Y_{jt}} \frac{dln(Q_{ijt})}{dt}$.[18] Given an initial value for Y_{jt}, then this measure of output will be uniquely determined by the values of Y_{ijt} and Q_{ijt}over time. We can then follow all of our previous steps with this alternative measure of industry output. Our analysis will not depend on the initial value we set for industries' output in an initial year.

There are different advantages from using this approach to measure industry output. First, as in previous studies measuring aggregate productivity growth with plant-level data (e.g., Levinsohn and Petrin (2012), hereafter LP), the contribution of changes in a firm's real output to aggregate value added is evaluated using current firm prices. Moreover, our measure of (marginal) industry productivity growth in this context can be derived from the framework proposed by LP to measure economy-wide productivity growth.[19]Second, this measure of industry output can be derived as a measure of industry real output in previous models used to study resource misallocation, where heterogeneous firms sell differentiated intermediate inputs. This will be the case if industry output is produced in a competitive market and is a CES aggregator of these intermediate inputs, as in the frameworks proposed by Hsieh and Klenow (2009) and Bartelsman, Haltiwanger, and Scarpeta (2013).[20]

In principle, one challenge for implementing our analysis in this context is the absence of extensive data on firm-specific prices P_{ijt} and real quantities Q_{ijt} across industries. However, under plausible assumptions, we can make inferences about our results with this industry output measure using our previous analysis, which do not require measuring P_{ijt} and Q_{ijt}. Our analysis of of geographically close markets using a difference-in-difference methodology also allows us to control for time and industry fixed effects. In addition, in Appendix A we show that if firms face the same elasticity of demand for their differentiated products ε_j within each industry then we have the

[18]A motivation for weighting firm output growth in this way is that prices might capture users' marginal valuation of differentiated goods.
[19] The framework proposed by PL allows one to measure the contribution of an industry to aggregate productivity growth, which might come from expanding industry aggregate factors. We are only interested in productivity gains conditional on the aggregate factors of an industry and show in Appendix A that our measure of industry productivity growth can be derived as a component of the PL measure that only captures this effect.
[20] Under these assumptions, real industry output growth will be given by the previous weighted average of firms' real output growth. Intuitively, firm-specific prices will measure the marginal rate of transformation between firm intermediate goods and industry output.

following results. Reallocation gains in this context are given by our previous gains multiplied by $\left(\frac{\varepsilon_j}{\varepsilon_j-1}\right)$. Moreover, we can decompose these gains in an analogous way to our previous case. In this decomposition, the sensitivity of resource reallocation to marginal products remains the same as before, and potential gains from reallocation can be obtained by multiplying our previous value by $\left(\frac{\varepsilon_j}{\varepsilon_j-1}\right)$.[21] Intuitively, these results all come from the fact that, for any given factor F, reallocation gains are now evaluated by replacing $\frac{\partial Y_{ijt}}{\partial F}$ with $P_{ijt}\frac{\partial Q_{ijt}}{\partial F}$ and $P_{ijt}\frac{\partial Q_{ijt}}{\partial F} = \frac{\partial Y_{ijt}}{\partial F}\left(\frac{\varepsilon_{jt}}{\varepsilon_{jt}-1}\right)$.[22]

2.4 Estimation of Production Functions

In order to implement the previous analysis, we need to first estimate the production function specified in equation (1) for each industry. We build on previous research in empirical industrial organization which explicitly addresses the simultaneity and selection biases involved in the estimation of production functions (Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2006)). Our analysis uses these estimates as inputs and does not imply anything about how these production functions should be estimated. We therefore consider a range of approaches to estimate production functions.

We consider both translog and Cobb-Douglas specifications. The key advantage of the translog specification is that it can be thought as a second-order approximation to any production function specified in (1). It does not impose the assumption that the factor elasticity of labor, capital and inputs are constant as the Cobb-Douglas does impose. Instead, it allows this elasticity to depend on firms' choices of all inputs. This is important as a factor's elasticity plays an important role in determining its marginal product and the central aspect of our analysis is modelling heterogeneity across firms in marginal products.

In our main results, we estimate (1) using the two approaches. First, we consider the approach proposed by Olley and Pakes (1996) (hereafter OP). We then consider extensions of this approach

[21] This assumption can be interpreted as an approximation and is common in recent models linking within-industry resource allocation to aggregate productivity (e.g., Hsieh and Klenow (2009) and Bartelsman, Haltiwanger, and Scarpeta (2013)).

[22] After presenting our initial evidence, we also measure differences in industry productivity using total differences in industry value added conditional on aggregate factors or differences in the weighted average of firm productivity in the industry (e.g., Olley and Pakes (1996)).

building on the insights of Levinsohn and Petrin (2003) and Ackerberg, Benkard, Berry, and Pakes (2006, hereafter ABBP). The approach in OP controls for the simultaneity and selection problems involved in the estimation of (1) by using a "proxy method" where one uses firms' investment decisions to construct proxies for their unobserved productivity parameters. Levinsohn and Petrin (2003) suggest using firms' choices of other inputs as proxy variables. ABBP discuss some of the issues with this approach and suggest directions to accommodate them. We build on these insights and extend the OP approach to use both investment and materials as proxy variables. We term this approach as LP.

We note that the explicit assumptions on primitives that we make when using these different approaches are consistent with the importance of financing frictions analyzed in this paper. A key assumption across these approaches is that one can uniquely pin down firm productivity, A_{ijt}, after conditioning on firms' choices and characteristics at time t. In the context of OP, this assumption means that there must be a unique mapping between firms' investment and its productivity at period t for firms with positive investment, after conditioning on its initial capital stock and age. This condition is consistent with the existence of financing frictions. While it does not allow firms' exposure to these frictions to be arbitrarily heterogeneous across firms, it allows this exposure to be a function of firm age, size and productivity.[23]

We estimate (1) separately for each 3-digit SIC code using plant-level panel data, which we describe in greater detail in Section 2. In our robustness analysis, we consider additional variations of OP, also discussed by ABBP, that rely on different assumptions. We also consider simple alternative approaches such as OLS regressions. Appendix B describes these approaches and their implementation in greater detail.

3 Data and Summary Statistics

Our main data sources are the Longitudinal Business Database (LBD), the Census of Manufacturers (CM) and the Annual Survey of Manufacturers (ASM) from the U.S. Census

[23] A simpler and alternative approach to estimate (1) is to assume that labor and materials factor shares are equal to their respective elasticity and recover the capital elasticity assuming constant returns to scale. However, this approach relies on the assumption that firms equate their marginal products of labor and materials to their respective factor costs. This assumption is inconsistent with the analysis in this paper, which is motivated by the existence of wedges between firms' marginal products of labor and labor costs (wages).

Bureau. The CM provides information on the sales and inputs used by all manufacturing firms every five years. Our analysis tracks over time the allocation of resources within industries across small firms, what requires data over time on a comprehensive number of small firms in these industries. Higher frequency data on small firms is useful in our analysis as it allows one to more precisely link changes in credit markets to changes in resource allocation. The ASM allows one to track this same information for a subsample of manufacturing firms in non-census years through rotating five-year panels. However, while large plants are sampled with probability one, small plants are sampled randomly with probabilities that decline with their size. When compared to samples of local industries in the CM, samples of local industries constructed in this way capture less than 10% of the firms of interest for our purposes. This issue is particularly relevant in the context of this paper because we need to measure within industry correlations over time. We address this challenge by combining the CM with the LBD. The LBD provides annual employment and payroll information for every private establishment from 1976 onward. The underlying data are sourced from U.S. tax records and Census Bureau surveys. We use the LBD to annually track over time the within-industry reallocation of labor and link to the CM to relate this reallocation to firm marginal products and firm productivities. We can only directly measure the reallocation of labor at an annual frequency, an issue that we explicitly address in our analysis. We measure firms' marginal products and productivities in a given year using data from the last available Census and address the potential measurement issues associated with this approach. We also use the LBD to track the entry and exit of firms.

We construct our initial data by matching single-plant firms in the LBD and CM. As previously discussed in Section 1.6, we focus on smaller single-establishment firms. Most establishments in manufacturing belong to a single-establishment firm. While these firms are small, in aggregate they represent close to 50% of the overall sales and employment of their industry-state on average across all years. Therefore, this sample of U.S. local industries captures a large portion of the U.S. economy.

Table 2 provides summary statistics on our main sample. It also provides information on the estimated average factor elasticity across factors and our different production function specifications. Additionally, it shows the within-industry dispersion of estimated marginal products and firm TFP across these different approaches. Since the methods outlined in Section

1.3 require panel data, we estimate the industry-level parameters of the production functions specified in (1) using the ASM. We construct our measures of marginal products and firm productivity by combining data from the CM with these estimated industry-level parameters. Variable definitions are in Appendix C.

4 Results

4.1 Labor Reallocation

Following our methodological framework, we examine how local credit market deregulation relates to changes in within-industry labor reallocation gains. We start by examining how the sensitivity of labor reallocation to the marginal product of labor in local industries relates to local credit market deregulation. A first approach to examine this relationship is to estimate:

$$\Delta EmpShare_{isjt} = \alpha_{sjt} + \beta_0 \times MPL_{isjt} + \beta_1 \times Dereg_{st} \times MPL_{isjt} + \delta \times X_{isjt} + \varepsilon_{isjt}, \quad (6)$$

where $\Delta EmpShare_{isjt}$ is the change in the employment share of firm i in industry j, state s and time t, $\alpha_{sjt}$is a state-industry-year fixed effect, MPL is the log of firm marginal product of labor, $Dereg$ is an indicator that equals one if credit market deregulation has been passed in the state and X denotes age controls. These controls age variables as well as their interaction with X. Employment share is the ratio of firm employment to the overall employment of a firm's industry-state. $\Delta EmpShare_{isjt}$ is measured as the log difference of this share between year *t* and *t-1*. Only firms present in the industry-state in both year *t* and *t-1* are included in the sample and the computation of the employment share.

Notice that $\beta_0$tells us the sensitivity of employment reallocation to the marginal product of labor for industries located in states that have not deregulated credit markets, i.e. it measures an average value of $LRSens_{jt}^1$ across these industries (See Section 1.2). Also notice that the state-industry-year fixed effects ensure that this relationship captures a correlation within an industry-state-year.

The coefficient of interest is $\beta_1$and tells us the differential value of this sensitivity for industries located in states with deregulated credit markets. The age controls X include the one-year lag of age, its squared value, as well as the interactions of both these variables with $Dereg$. There are important life-cycle patterns in productivity, and we want to capture differences between the marginal products of firms at the same stage of their life cycle.

One potential issue with this approach is that β_1 might be capturing cross-state differences and times-series trends in the employment reallocation of industries. We address these issues by controlling for both fixed differences across states and time-series changes in the employment reallocation of local industries. This is done by adding state and year fixed effects interacted with MPL as controls in the estimation of (7). After we add these controls, the estimation of β_1 can be thought as a difference-in-differences estimation of how state credit market deregulation affects the labor reallocation sensitivity of local industries. Intuitively, one can think about this estimation as involving two steps. First, we estimate the sensitivity of labor reallocation to the marginal product of labor within each industry-state-year. We then estimate how deregulation affects this relationship using a difference-in-differences specification. We are implementing these two steps together in a single regression.[24] If differences in the timing of deregulation across states capture long-term differences across them, as argued by Krozsner and Strahan (1999), this approach will isolate the impact of deregulation on $LRSens$.

In addition to these controls, we also include firm fixed effects to control for fixed differences across firms in their employment growth. This leads us to estimate:

$$\Delta EmpShare_{isjt} = \alpha_{sjt} + \mu_i + \gamma_s \times MPL_{isjt} + \theta_t \times MPL_{isjt} \qquad (7)$$

$$+\beta_1 \times Dereg_{st} \times MPL_{isjt} + \delta \times X_{isjt} + \varepsilon_{isjt},$$

where μ_i denotes firm fixed effects, θ_t denotes year fixed effects, γ_s denotes state fixed effects, and the other variables are defined as in equation (6).

Table 3 reports results of the estimation of equations (7) and (8). We consider both intrastate and interstate credit market deregulation episodes, and use both translog and Cobb-Douglas

[24] Notice that the sample of firms used to estimate this relationship is changing over time and can be affected by deregulation. Motivated by our analysis in Section 1, we are interested in analyzing how an industry measure ($LRSens$) changes with credit market deregulation. At any given year, this measure has to be computed using all existing firms in an industry.

production function specifications. Furthermore, we estimate these production functions based on both the OP and LP approaches. Panel A of Table reports the estimated coefficients for β_1, which capture changes in $LRSens$. Panel B of Table 3 quantifies the magnitude of the percentage changes in $LRSens$ implied by these effects. We compare our estimates for β_1 to the average sensitivity of employment reallocation to the marginal product of labor prior to deregulation. We find that local credit market deregulation is associated with both economically and statistically significant differences in the sensitivity of labor reallocation to the marginal product of labor. We find that credit market deregulation leads to percentage increases in $LRSens$ between 27%-32% and 46%-49% in the context of intrastate and interstate deregulation episodes, respectively. This evidence suggests that credit market deregulation is associated with significant changes in the extent to which industries reallocate resources in response to a given gap in marginal products.

4.2 Potential Gains from Reallocation

We now examine whether credit market deregulation is associated with changes in the potential reallocation gains in equation (5). As equation (5) illustrates, reallocation gains are the product of potential gains and $LRSens$. We examine the extent to which credit market deregulation is associated with percentage changes in potential labor reallocation gains. By combing these results with our previous estimates for the percentage changes in $LRSens$, we can analyze the extent to which credit market deregulation is associated with overall changes in labor reallocation gains. One reason to expect changes in potential reallocation gains is that, as resources move towards higher marginal product firms, marginal products might become more equalized across firms. However, in practice, the significance of this effect is unclear for at least two reasons. First, the extent to which labor reallocation feedbacks into lower dispersion in firm marginal products will depend on the curvature of production functions and how firms adjust other factors.[25] Second, credit market deregulation might also affect the distribution of firm productivity in an industry, for example, because of changes in individual firm-level productivity.

We address this issue by estimating:

[25] For example, if firms adjust all factors together and returns to scale are close to one, then there will be a limited drop in the dispersion of firms' marginal products.

$$Log(Potential\,LRG)_{sjt} = \alpha_{sj} + \theta_t + \beta \times Dereg_{st} + \varepsilon_{sjt}, \tag{8}$$

where $Potential\,LRG$ are potential labor reallocation gains in industry j, state s, and time t, $\alpha_{sj}$is a state-industry fixed effect, θ_t are year fixed effects, and $Dereg_{st}$ is defined as before. This approach is similar to the one in our previous results where our analysis is equivalent to estimating a difference-in-differences specification with $LRSens$.

Table 4 reports the results. We find that percentage changes in potential reallocation gains are significantly smaller in magnitude than our previously estimated the percentage increases in$LRSens$. For example, in the case of interstate deregulation we estimate drops in $Potential\,LRG$ between 5-8% and increases in $LRSens$ between 45%-49%.We conclude that the percentage changes in $LRSens$ associated with credit market deregulation mostly translate into percentage increases in labor reallocation gains. Therefore, credit market deregulation is associated with significant percentage changes in labor reallocation gains and this effect is driven by changes in the sensitivity of reallocation to marginal products.

4.3 Quantifying Cumulative Productivity Gains from Changes in Labor Reallocation

We quantify the cumulative industry productivity gains implied by these changes in marginal labor reallocation gains. We quantify these gains by considering the contribution of resource reallocation to cumulative changes in industry productivity over a given period of time. More precisely, we want to analyze the difference between the realized growth rate of industry value added between years t and $t+\tau$ and the growth rate we would have observed in the absence of any changes in factor shares over these years. As in our previous analysis, we evaluate this difference conditional on other determinants of changes in industry output and at constant industry output prices. More specifically, as before, we hold constant changes over time in industry total factors and firm-level productivity. We now explicitly consider entry and exit decisions, which will change the composition of firms over time. This additional growth in industry value added between years t and $t+\tau$ will capture the contribution of resource reallocation in the intensive margin to changes in industry productivity over this period. Let $VA_j(t, t+\tau)$ denote this value-added contribution, measured at $t+\tau$ industry output prices. Let also $RG_{js} = LRG_{js} + KRG_{js} + MRG_{js}$ denote a discrete time approximation for our previous reallocation gains, computed in the sample of firms that exist in the industry in both years s and $s-1$. In Appendix A we show that, under plausible conditions, a first-order approximation for $VA_j(t, t+\tau)$ is given by:

$$VA_j(t, t+\tau) \approx \left(\frac{1}{1-sm_{jt+\tau}}\right)(1-s)\left(RG_{jt+\tau} + \delta RG_{jt+\tau-1} + \cdots + \delta^{\tau-1} RG_{jt}\right), \quad (9)$$

where s is the share of new entrants in the industry's output, $\delta = \frac{(1-s)\theta}{1+\mu}$, θ captures the persistence of firm productivity and μ is the growth rate of firm-level productivity.[26] In general, all these parameters can change by year. We have set them as constant for expositional simplicity.

Intuitively, differences in resource reallocation over time only matter by affecting the final allocation of resources in year $t+\tau$, and their impact on industry output in year $t+\tau$ needs to be evaluated using the values of firm productivity in that same year. Equation (9) illustrates the different reasons to expect a reallocation gain today to have an impact on the future level of industry productivity that goes away over time. First, the distribution of productivity across existing firms in an industry will change over time. For example, if differences in firm productivity within an industry today are uncorrelated with differences in firm productivity in ten years, then reallocation gains taking place today should not affect the level of industry productivity in ten years. Second, gains from reallocating resources across existing firms in an initial year might diminish in importance in future years, as entry and exit reduce the importance of the initial firms in the industry. Additionally, the existence of firm-level productivity growth will lead to intensive margin changes in output even in the absence of reallocation. Percentage output gains due to reallocation in the past will represent a smaller percentage of future output. These effects are captured by the discount rates θ, $1-s$, and $\frac{1}{1+\mu}$, respectively. These discount rates capture simple moments in the data that we directly measure.

We use Equation (9) to compute the cumulative gains over the sample due to the greater labor reallocation gains associated with credit market deregulation. More specifically, we determine the discount rates in Equation (9) using moments from our overall sample.[27] We estimate additional reallocation gains using our estimated percentage changes in these gains combined with the

[26] The approximation comes from the fact that we use first-order approximations for the output growth of the industry in each year.
[27] We have found that differences in these moments between state-year observations with and without credit market deregulation are not economically important for this exercise.

average value of these gains prior to deregulation. For each type of deregulation episode, we accumulate these effects over the average number of deregulated years in the sample. On average, states have credit markets that already passed interstate and intrastate deregulation during 7.3 and 14.8 years in our sample, respectively. As discussed in Section 1, we consider two measures of industry output and equation (9) captures these gains using our first measure. We translate reallocation gains using this first measure into gains with our second measure by scaling them by $\left(\frac{\varepsilon}{\varepsilon-1}\right)$, where ε is the average demand elasticity for firms' products across industries. The literature tends to use values for the average demand elasticity between three and five and we set this value equal to four.[28]

Table 5 reports the magnitudes of cumulative productivity gains across different specifications and industry productivity measures. We denote these gains computed with our first and second measures of industry output as *Industry Productivity Gain_1* and *Industry Productivity Gain_2*, respectively. Panel A of Table 5 reports estimates of these magnitudes using all industries in our sample. The magnitudes of productivity gains are significantly more important for interstate deregulation episodes.[29]Notice that our goal is examine if *some* significant reform in credit markets leads to substantial reallocation gains. Our null hypothesis is that the reallocation channel is not quantitatively important and, therefore, reforms in credit markets cannot lead to sizeable productivity gains through this channel. We estimate that the increase in labor reallocation gains associated with interstate deregulation leads to an increase in the value-added of local industries between 1.5% and 2.0% over a horizon of approximately seven years. To place these estimates in perspective, we note that Hsieh and Klenow (2009) estimate that fully equalizing firms' marginal products across all factors in the U.S. manufacturing sector during the late 1980s would lead to increases in industry productivity of approximately 31%. These estimated gains are directly comparable to the ones based on our measure *Industry Productivity Gain_2*. Relative to this benchmark, our results suggest that, in seven years, changes in labor reallocation associated with interstate deregulation generate approximately 6.5% of possible long-term gains from reallocating all production factors.

[28] For example, see Hsieh and Klenow (2009), Bartelsman, Haltiwanger, and Scarpeta (2013), and Asker, Collard-Wexler, and De Loecker (2014). Using the previous expression, it is simple to see that our estimates will be not very sensitive to different choices within this range of values.
[29]This is consistent with Cetorelli and Strahan (1996) that provide evidence that interstate deregulation episodes matter more for small manufacturing firms.

We note that this gain is an average across all U.S. local industries and that the scope for such reallocation gains is likely to be smaller in the U.S. than in other settings. Indeed, the U.S. is used as a low frictions benchmark to calibrate the model in many studies of misallocation (e.g., Hsieh and Klenow (2009)). We then evaluate our previous magnitudes on a subset of local industries where the scope for such gains is predicted to be larger. We argue that the effect in such industries is more likely to be representative of effects in environments outside the U.S. where resource misallocation issues are likely to be more pronounced. We predict the scope for such gains using two criteria. First, we restrict our sample to industries in the top 50% and 33% of potential gains from reallocation prior to deregulation. Intuitively, these are industries with greater dispersion in marginal products. Second, we implement this analysis only among industries in the top tercile of estimated returns to scale. As previously discussed, the impact of changes in within industry resource reallocation might be mitigated by drops in the potential gains from reallocation, and this effect is likely to be less relevant in such industries. In this subsample, average estimated returns to scale are approximately 0.95. The final subsamples in these results represent between 17% and 11% of our initial sample.

In each of these exercises, we follow our previous steps, examining both percentage changes in $LRSens$ and potential gains from labor reallocation and then compute the magnitude of cumulative industry value added gains. As in our previous results, we found significant increases in $LRSens$ and no evidence of significant drops in the potential gains from reallocation in these subsamples. Panels B to D of Table 5 report the magnitude of the cumulative productivity gains implied by these effects. The magnitude of these gains in the overall sample of higher returns to scale is similar to the one in our previous results. Panel C shows that the economic magnitudes of these gains in industries with high potential reallocation gains is associated with productivity gains between 3.3% and 4.4% of industry value – significantly larger than the gains in the overall sample.

Together, this evidence suggests that the productivity gains due to labor reallocation after credit market deregulation are significant for the average U.S. industry and are economically large for an important subset of U.S. industries with high dispersion in marginal products and close to constant returns to scale.

4.4 Incorporating the Reallocation of Other Production Factors

We now incorporate potential productivity gains from the reallocation of other factors. Under additional assumptions, we can infer reallocation gains across all factors from the reallocation of labor.[30] These additional assumptions are the following. First, firms' industry shares of factors are constant across factors. In the Internet Appendix, we provide direct evidence that, within our sample of small firms, industry shares across factors are close to constant for a given firm. Second, plants' returns to scale must be close to one. We address this issue by restricting our analysis to industries with estimated returns to scale close to one. Our previous results suggest that labor reallocation gains are similar in this subset of industries. In Appendix A we show that, under these conditions, we can write industry productivity growth using our first output measure as $IPG_{jt} = \left(\frac{1}{1-sm_{jt}}\right)\left(\frac{dln(A_{jt})}{dt}\right)$, where A_{jt} is a weighted average of firm productivity across the industry's existing firms. This average is a commonly used measure of industry productivity in the literature (e.g, Oley and Pakes (1996)) and the weights used to compute A_{jt} are the industry shares of any production factor. In our analysis we use labor. Moreover, let $RG_{jt} = LRG_{jt} + KRG_{jt} + MRG_{jt}$ denote reallocation gains across all factors. In Appendix A, we also show that, under these conditions, we can write these gains as $RG_{jt} = \frac{1}{A_{jt}} \sum_{i \in I_{jt}} A_{ijt} \frac{dSL_{ijt}}{dt}$. Intuitively, we can now evaluate reallocation gains using firm productivity, as opposed to marginal products. We can also further decompose these gains in a similar way to equation (5):

$$RG_{jt} \approx \frac{Var(A_{ijt})}{E(A_{ijt})} \frac{1}{A_{jt}} TFPSens_{jt}, \qquad (10)$$

where $TFPSens_{jt}$ is defined analogously to $LRSens_{jt}$ by replacing the marginal product of labor with firm tfp. This measure captures the extent to which industries reallocate resources towards higher tfp firms. The term $\frac{RG_{jt}}{TFPSens_{jt}}$ captures the potential gains from reallocating all factors.

We follow the same steps used in our previous results in this context. We first estimate:

$$\Delta EmpShare_{isjt} = \alpha_{sjt} + \mu_i + \gamma_s \times TFP_{isjt} + \theta_t \times TFP_{isjt} \qquad (11)$$

[30] We have also directly examined capital reallocation gains and found evidence that incorporating these effects amplifies our previously estimated labor reallocation gains. One major challenge in following this approach is that we need to restrict our sample to the four years in which there was a Census of Manufacturers: 1977, 1982, 1987 and 1992. As discussed in Section 2, our analysis requires tracking a large number of small firms. This reduces the precision of our estimates and makes it harder to identify the impact of deregulation episodes.

$$+\beta_1 \times Dereg_{st} \times TFP_{isjt} + \delta \times X_{isjt} + \varepsilon_{isjt},$$

where $TFP_{isjt}$is firm TFP, and all other variables are defined as in equation (8). We then estimate the implied percentage changes in $TFPSens_{jt}$ and combine them with direct estimates of percentage changes in potential reallocation gains. Finally, we use equation (6) to estimate the cumulative productivity gains associated with changes in the reallocation of all factors.

Panel A of Table 6 reports results from the estimation of equation (11) and the implied magnitudes for the percentage changes in $TFPSens_{jt}$.We find that deregulation is also associated with significant increases in $TFPSens_{jt}$. The percentage increase in this sensitivity is estimated to be 17.8% and 50.5% in the context of intrastate and interstate deregulations, respectively. Panel B of Table 6 shows that these changes in $TFPSens_{jt}$ are associated with much smaller and statistically insignificant changes in the potential gains from reallocating factors. As before, changes in resource reallocation translate into significant percentage increases in marginal reallocation gains.

Finally, Table 7 computes the same magnitudes analyzed in Table 5 in the context of this analysis. These magnitudes now capture productivity gains from reallocating all factors, as opposed to only gains from reallocating labor. Overall, the magnitudes in this analysis are larger than the magnitudes reported in Table 5. For example, we now estimate that interstate deregulation leads to cumulative value added gains between 2.8% and 3.7%. These results now imply that changes in factor reallocation associated with interstate deregulation generate approximately 10.5% of all possible long-term gains from reallocation. We also estimate these gains in the industries with the largest productivity differences and thus the largest potential productivity gains. In the subsample of industries in with high productivity dispersion, the results imply that interstate deregulation leads to productivity gains between 4.7% and 6.2% of industry value added.

Together, these findings suggest that our previous labor reallocation gains play an important role in determining the overall effect of credit market deregulation on aggregate productivity through the reallocation of production factors.

5 Robustness

Our analysis relies on two key ingredients. First, there is an identification concern. We need to be able to empirically identify the effect of credit market deregulation on industry outcomes and credit market deregulation cannot be correlated with other state-level changes that affect the relative growth of higher marginal product firms. Second, we need to measure gaps in the marginal products of firms. This raises a misspecification concern. We extensively address each of these concerns in the context of our previous labor reallocation results. In this analysis, we focus on interstate deregulation episodes, where we found our strongest effects.[31]

5.1 Identification Concerns

Our analysis requires isolating the impact of changes in credit markets on the differential growth of higher marginal product firms. An identification concern is that this relative growth may be correlated with other state-level changes. We first address this identification concern in the context of our previous methodology. We start by examining trends in $LRSens$ prior to credit market deregulation. We analyze this issue by adding $Dereg(-1\ to -5)$ to the estimation of (8). This variable is an indicator that equals one in the five years prior to deregulation and is included in an analogous way to $Dereg$. Columns (1) and (2) in Panel A of Table 8 show that states do not experience differential changes in $LRSens$ in the five years prior to deregulation. Figure 1 breaks down this effect across the five years prior to deregulation, normalized by our previously estimated effects associated with $Dereg$. These results further show that deregulation is not associated with a positive differential trend in $LRSens$ in the years prior to deregulation. These results provide support to the view that deregulation is not capturing previous positive trends differentially affecting higher marginal product firms within local industries.

Second, we refine our previous estimates and comparing only industries located in the same Census region. One can think of these results as estimating the previous effects for each of these five regions and then averaging the effects across the five cases. The previous identification assumption now only needs to be applied to the timing of deregulation within each region. Columns (3) and (4) in Panel A of Table 8 shows these results, which are estimated by adding region-year fixed effects and their interaction with MPL as additional controls in the estimation of

[31] To the extent that these effects do capture the impact of deregulation, they should be more easily detected in refined results. An additional reason to focus on interstate deregulation when addressing identification concerns is this analysis requires many deregulation episodes during our sample with data available for many years prior to deregulation.

(8). These coefficients are directly comparable and similar to the ones in columns (5) and (6) in Panel B of Table 3. These results show that our findings are robust to applying our previous identification assumption only to the timing of deregulation within each region.

Our third way to address the identification concern is to use a matching approach. We identify local industries that experienced deregulation in their states and construct a matched sample of geographically close industries in adjoining states that did not experience deregulation over that same period. An example would be examining the Washington area SMSA and comparing the same industry in the adjacent states of Maryland and Virginia. We then examine if the sensitivity of labor reallocation to the marginal product of labor differentially changed in treated industries, when compared to matched industries, around the time of their deregulation episode.

For each industry that experiences deregulation during our sample, we construct a group of matched industries in the following way. We find the ten closest industries in the same 2-digit SIC code and Census region but in different states that did not experience a deregulation episode around the treated industry's episode. More precisely, we only consider industries that did not experience a deregulation episode in a seven-year period centered in the treated industries' deregulation year. We measure the distance between two local industries as the average distance between their plants. We construct different samples of matched industries, which impose different constraints on the maximum allowed distance between treated and control industries.

This approach is motivated by the idea that, among the small manufacturing firms in our sample period, credit markets are more local than product markets. Petersen and Rajan (2002) estimate that the average distance between small firms and their bank lenders is approximately 50 miles during our sample period. Moreover, their estimate for this distance in early 1990s is 68 miles. Using plant level data from the commodity flow survey, Holmes and Stevens (2012) estimate average shipment distances for manufacturing plants in the size range of our sample between 330 and 420 miles in 1997. Therefore, if control and treated industries are geographically close within a certain distance range, they are arguably exposed to different credit markets but face similar product market conditions.

Motivated by these previous numbers, we exclude industries closer than 50 miles from treated industries while constructing control industries. We also impose different upper bounds on their distance to treated industries. By imposing upper bounds of 1,000 and 500 miles, we construct two groups of treated and control industries with average distances equal to 292 and 215 miles, respectively. In each of these samples, we have found that most treated and control industries have a distance below these average values. We denote these samples of treated and control industries as *Sample_1* and *Sample_2*, respectively.

After constructing these samples of matched treated and control industries for each interstate deregulation episode, we estimate the following specification:

$$\Delta EmpShare_{isjct} = \alpha_{sjct} + \alpha_0 \times Treated_c \times MPL_{isjt} + \alpha_1 \times Post_{ct} \times MPL_{isjt} \quad (12)$$

$$+ \beta \times Treated_c \times Post_{ct} \times MPL_{isjt} + \delta \times X_{isjct} + \varepsilon_{isjct},$$

where $\Delta EmpShare_{isjt}$ is the change in the employment share of firm i in industry j, state s, time t, and episode c. The deregulation of the credit markets faced by each industry-state is indexed as a separate episode c. For any given episode, both the treated industry and the matched controls for that episode are included and the data covers a seven-year period centered in the deregulation year of the treated industry. The data for all episodes is then stacked. Notice that, by construction, control industries do not experience deregulation during a given episode. Therefore, a given industry-state-year cannot be used as treated local industry in one episode and a control local industry in another episode. However, it might be used as a control for different episodes and appear multiple times in the data.[32]

The remaining variables are defined as follows. α_{sjct} is a state-industry-episode-year fixed effect, $Treated$ is an indicator that equals one for the treated industry in a given episode, $Post$ is an indicator that equals one during the years after the treated industry's deregulation, MPL is the log of firm marginal product of labor, and X denotes age controls.

The coefficient of interest is β and tells us whether the sensitivity of labor reallocation to the marginal product of labor differentially changes in treated industries after their deregulation, relative to geographically and economically close control industries. As in the context of equation (8), one can think about the estimation of this effect as capturing a differences-in difference

[32] We address the implications of this issue for statistical inference by clustering standard errors at the industry level.

estimator of changes in $LRSens$ around deregulation. The central difference between these results and our previous results is the choice of the control groups. In the previous results, for each industry in a state that deregulated credit markets, we used all other industries that did not pass deregulation around that time as controls. Another important difference is that we are focusing now on shorter window around deregulation dates.[33]

Panel B of Table 8 reports the results. We find a significant increase in $LRSens$ for treated industries versus control industries in the years immediately following deregulation. The magnitude of this increase is directly comparable and similar to the ones in columns (5) and (6) in Panel B of Table 3. This magnitude is also stable across different specifications using alternative distances between treated and control industries.

As a final check on this analysis, we formally test whether treated and control industries have differential trends in labor reallocation prior to deregulation. We extend our previous sample to six years prior to deregulation years and keep only control industries that did not experience deregulation over these additional years. We use the upper bound of 1,000 miles to maximize our sample size. Panel C of Table 8 reports these results, which show no statistically significant difference in pre-trends between treated and control industries. Prior to deregulation, treated industries experience lower increases in $LRSens$, and these differences are economically small when compared to the effects in the opposite direction after deregulation.

Together, this evidence provides support to the view that our previous evidence on increased reallocation gains after interstate deregulation captures the effect of banking deregulation.

5.2 Measurement of Marginal Products

We implement several robustness checks to address the concern that we might not be accurately measuring differences or gaps in the marginal product of firms. We first consider alternative approaches to estimate the production function specified in (1).[34] Following the discussion in Ackerberg, Benkard, Berry, and Pakes (2006), we modify the OP approach to allow

[33] Note that the group of treated industries is essentially the same as before, as almost all states passed interstate deregulation in the middle of our sample.
[34] Note that the translog production function can be thought as a second-order approximation to any production function specified in (1).

labor as a dynamic input.[35] We label this estimation approach as OP2. We also consider simple alternative approaches to estimate (1). More specifically, we consider OLS regressions with only time fixed effects and panel data estimates including plant and time fixed effects. We label these estimation approaches as OLS and FE, respectively. Panel A and B of Table 9 reports results replicating the estimates of Table 3 with these different approaches. We find that credit market deregulation is associated with percentage increases in the sensitivity of labor reallocation to marginal products that are similar to the ones in our previous results. In the Internet Appendix we show that, as in our previous results, these increases in $LRSens$ are associated with much smaller and statistically insignificant changes in the potential gains from reallocation. Panel C of Table 9 then quantifies the magnitude of productivity gains implied by these effects, following the same steps used in Table 5. For expositional simplicity, we focus only on the magnitudes for the average industry in the sample and normalize the estimated magnitudes by the average of respective values in Table 5. These results suggest that our previous magnitudes are robust across a range of approaches for the estimation of (1).

We then consider value-added production functions. In this approach, since we measure value added directly, we do not need to adjust changes in industry output with the $\left(\frac{1}{1-sm}\right)$ term as we did in Section 1. In this approach, differences in industry productivity simply capture gaps in the total value added of industries given the same aggregate factors.[36] We estimate value-added production functions also using translog and Cobb-Douglas specifications, as well as the OP, OLS and FE estimation approaches. Table 10 reports these results in an analogous way to Table 9. The results show that credit market deregulation is associated with larger percentage increases in the sensitivity of labor reallocation to marginal products when marginal products are estimated using value-added production functions. In the Internet Appendix we show once more that these increases in $LRSens$ are associated with smaller changes in the potential gains from reallocation. Moreover, the magnitudes of productivity gains estimated with this approach are similar to and approximately 30 percent larger than the ones estimated in Table 5.

An additional concern with our measurement of marginal products is that a higher marginal product of labor might be capturing a more skilled workforce. According to this view, our main

[35] See Appendix B for a more detailed discussion of the assumptions made across these estimation approaches.
[36] In contrast to our main results, differences in value added here are not measured at constant industry output prices.

results capture a differential increase in the growth of firms using higher skilled labor after credit market deregulation. We note that, in contrast with this view, previous research has provided evidence that these same deregulation episodes lead to an increase in the demand for unskilled labor (Beck, Levine, and Levkov (2010)). We then directly address this possibility using average worker wages in a firm as a control for average worker skill. Previous research has suggested that wage differentials across workers capture mostly worker characteristics, as opposed to firm characteristics. More specifically, we include firm wages controls in the estimation of an analogous way to firm age controls in the estimation of equation (8). Since previous research has suggested that wage differentials are positively correlated with firm productivity, this approach might lead us to underestimate the importance of labor reallocation gains. Table 11 report results following this approach. We find that both percentage increases in $LRSens$ and the magnitude of productivity gains implied by these changes remain similar to the ones in Table 3 and 5. These results suggest that differences in worker skill across firms are unlikely to be driving our previous findings.

A final concern with our measurement of marginal products comes from the fact that, as previously discussed in Section 2, we measure firms' marginal products using data from the last available Census of Manufacturers. We note that the average distance between the last census and the current year in our sample is two years. In the Internet Appendix, we provide direct evidence that differences in marginal products within an industry are highly persistent at such horizon and also find that our analysis is robust to including only years which are closer in time to the years in which marginal products are measured. These findings suggest that this source of misspecification does not significantly affect our analysis.

6 Alternative Channels

We close our analysis by considering alternative channels through which credit market deregulation might affect the aggregate productivity of local industries. We consider firm-level productivity changes and extensive margin changes through entry and exit decisions. Because of space limitations, we only report our main findings and discuss our basic approach. We show our analysis in more detail in the Internet Appendix.

We first consider changes in firm-level productivity. Previous research has provided evidence that credit market deregulation is associated with increases in firm-level productivity (Krishnan, Nandi, and Puri (2014), hereafter KNP). One interpretation for such effect is that financing constraints limit firms' ability to adopt different technologies or management practices. We use a differences-in-difference specification to examine how deregulation is associated with changes in the productivity of a given firm in our sample.[37] We find that interstate deregulation is associated with increases in firm-level productivity, with magnitudes similar to the one reported in KNP. We then quantify the cumulative increases in industry value added through this channel after interstate deregulation. Panel A of Table 12 reports these results for the average industry in our sample. These results are directly comparable to our previous estimates for *Industry Productivity Gain_1*. When compared to our previous reallocation effects, these firm-level effects are the same sign but smaller in magnitude. These estimates suggest that the intensive margin productivity increases associated with deregulation mostly capture reallocation gains. Moreover, we have found no significant differences in these firm-level effects for the subset industries where we found larger reallocation effects. These findings emphasize the importance of studying the implications of financing frictions for productivity at the industry level, as opposed to only at the firm level.

These two previous channels capture the intensive margins through which industry productivity can change. We also extend our analysis to capture potential effects of credit market deregulation on industry productivity through extensive margin effects due to changes in firms' entry and exit decisions. In the interest of space, we present these results in the Appendix A. Under the assumptions discussed in Section 3.4, we can write our first measure of industry output as $Y_{jt} = A_{jt}H(K_{jt}, L_{jt}, M_{jt})$, where $A_{jt} = \sum_{i \in I_{jt}} \frac{L_{ijt}}{L_{jt}} A_{ijt}$ is a measure of industry productivity or total factor productivity. As discussed in Section 3.4, we can address the assumption of constant returns to scale by restricting our analysis to industries with estimated returns to scale close to one. Once we have this simple measure of industry productivity, we can build on previous dynamic decompositions which isolate the contributions of resource reallocation in both the intensive and extensive margins to industry productivity growth (e.g., Foster, Haltiwanger, and Kriznan (2001)). Summarizing these results, we find changes in entry and exit along the lines of Nanda and Kerr

[37] Krishnan, Nandi, and Puri (2014) also analyze the effect of state banking deregulation but focus on measures taken by states to limit their exposure to national legislation allowing banks to operate across states from 1994 on.

(2009). However, also consistent with their findings, our results suggest that these effects had a limited impact on industry productivity growth. One simple explanation for these findings is it can be hard to predict the quality of new firms before they start operating and producing results. Therefore, changes in credit markets have a limited impact in improving the selection of firms at birth and matter more by shaping this selection at later stages.

7 Conclusions

We study how the deregulation of local credit markets in the U.S. affects the aggregate productivity of local industries by shaping the allocation of labor among firms, a channel we label as reallocation channel. We find that the deregulation of these local U.S. credit markets through the state banking deregulation leads to significant increases in the reallocation of labor within local industries towards firms with higher marginal products. We propose an approach to quantify the industry productivity gains from such increased reallocation by estimating firm marginal products and firm productivity using plant-level data.

We find that these reallocation effects through labor lead to significant increases on the aggregate productivity of the average U.S. industry. Moreover, these effects can be economically large for an important set of industries where such effects are predicted to be larger. Across a range of tests, we show that our results are robust to extensive checks addressing the two essential requirements for our analysis. Namely, measuring gaps in firms' marginal products and isolating the effect of credit market deregulation. Our results are robust to conducting a difference-in-difference approach in geographically close markets that span states that have deregulated at different times. Finally, we also compare these effects to changes in industry productivity after credit market deregulation through other channels including the entry of new firms. We find evidence that the reallocation channel is significant when compared to these other channels.

Overall, our analysis suggests that the labor reallocation channel can be economically important even in the United States which has relatively well-developed financial markets and where resource misallocation is often believed to be limited. The economic significance of these effects for industries more likely to face misallocation suggests that, more broadly, changes in credit markets can have a first-order impact on aggregate productivity through changes in the intensive margin and the reallocation of resources towards more productive firms.

Our results not only suggest the quantitative importance of the reallocation channel, but also have additional implications. For example, they suggest that reallocation effects through labor, not only capital, can be important. They also suggest that, at least during the U.S. banking deregulation experience, changes in credit markets matter more by affecting resource allocation at later stages of firms' life cycle versus at the selection of firms at their birth.

References

Ackerberg, D., L. Benkard, S. Berry, and A. Pakes, 2007, Econometric Tools for Analyzing Market Outcomes, *Handbook of Econometrics* 6, 4171-4276.

Agrawal, A., and D. Matsa, 2013, Labor Unemployment Risk and Corporate Financing Decisions, *Journal of Financial Economics* 108, 449-470.

Amil, D., 1993, State Laws Affecting the Geographic Expansion of Commercial Banks, unpublished manuscript, Board of Governors of the Federal Reserve System.

Asker, J., A. Collard-Wexler, and J. De Loecker, 2014, Dynamic Inputs and Resource (Mis)Allocation, *Journal of Political Economy* 122, 1013-1063.

Basu, S., and J. G. Fernald, 2002, Aggregate Productivity and Aggregate Technology, *European Economic Review* 46, 963-991.

Bartelsman, E., J. Haltiwanger, and S. Scarpetta, 2013, Cross-Country Differences in Productivity: The Role of Allocation and Selection, *American Economic Review* 103, 305-34.

Beck, T., R. Levine, and A. Levkov, 2010, Big Bad Banks? The Winners and Losers from Bank Deregulation in the United States, *Journal of Finance* 65, 1637-1667.

Beck, T., R. Levine, and N. Loayza, 2000, Financial Intermediation and Growth: Causality and Causes, *Journal of Monetary Economics* 46, 3-77.

Benmelech, E., N. Bergman, and A. Seru, 2011, Financing Labor, NBER Working Paper 17144.

Bertrand, M., A. Shoar, and D. Thesmar, 2007, Banking Deregulation and Industry Structure: Evidence from the French Banking Reforms of 1985, *Journal of Finance* 62, 597-628.

Brown, J. and D. Matsa, 2013, Boarding a Sinking Ship? An Investigation of Job Applications to Distressed Firms, Working Paper.

Buera, F. J., J. P. Kaboski, and Y. Shin, 2011, Finance and Development: A Tale of Two Sectors, *American Economic Review* 101, 1964-2002.

Cetorelli, N., and P. E. Strahan, 2006, Finance as a Barrier to Entry: Bank Competition and Industry Structure in Local Markets, *Journal of Finance* 61, 437-461.

Chodorow-Reich, G., 2014, The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-2009 Financial Crisis, *Quarterly Journal of Economics* 129, 1-59.

Collard-Wexler, A., and J. De Locker, 2014, Reallocation and Technology: Evidence from the U.S. Steel Industry, *American Economic Review,* forthcoming.

Foster, L., J. Haltiwanger, and C. J. Krizan, 2001, Aggregate Productivity Growth. Lessons from Microeconomic Evidence, *NBER Chapters, in: New Developments in Productivity Analysis*, 303-372 National Bureau o Economic Research, Inc.

Foster, L., J. Haltiwanger, and C. Syverson, 2008, Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?, *American Economic Review* 98, 394-425.

Guiso, L., L. Pistaferri, and F. Schivardi, 2013, Credit Within the Firm, *Review of Economic Studies* 80, 211-247.

Holmes, T. J., and J. J. Stevens, 2012, Exports, Borders, Distance, and Plant Size, *Journal of International Economics* 88, 91-103.

Hsieh, C., and P. J. Klenow, 2009, Misallocation and Manufacturing TFP in China and India, *Quarterly Journal of Economics* 124, 1403-1448.

Jayaratne, J, and P. E. Strahan, 1996, The Finance-Growth Nexus: Evidence from Bank Branch Deregulation, *Quarterly Journal of Economics* 111, 639-670.

Kerr, W. R., and R. Nanda, 2009, Democratizing Entry: Banking Deregulations, Financing Constraints, and Entrepreneurship, *Journal of Financial Economics* 94, 124-149.

Krishnan, K., D. Nandy, and M. Puri, 2014, Does Financing Spur Small Business Productivity? Evidence from a Natural Experiment, *Review of Financial Studies,* forthcoming.

Kroszner, R. S., and P. E. Strahan, 1999, What Drives Deregulation? Economics and Politics of the Relaxation of Banking Branching Restrictions, *Quarterly Journal of Economics* 114, 1437-1467.

Larrain, M., and S. Stumpner, 2013, Capital Account Liberalization and Aggregate Productivity: The Microeconomic Channels, unpublished manuscript, Columbia Graduate School of Business.

Levine, R., 1997, Financial Development and Economic Growth: Views and Agenda, *Journal of Economic Literature* 35, 688–726.

Levinsohn, J, and A. Petrin, 2003, Estimating Production Functions Using Inputs to Control for Unobservables, *Review of Economic Studies* 70, 317-342.

Matsuyama, K., 2007, Aggregate Implications of Credit Market Imperfections, *NBER Macroeconomics Annual 22*, (eds. D. Acemoglu, K. Rogoff, and M. Woodford).

Melitz, M., 2003, The Impact Of Trade On Intra-Industry Reallocations And Aggregate Industry Productivity, *Econometrica* 71, 1695-1725.

Midrigan, V., and D. Y. Xu, 2014, Finance and Misallocation: Evidence from Plant-Level Data, *American Economic Review* 104, 422-458.

Moll, B., 2014, Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation?, *American Economic Review* 104, 3186-3221.

Olley, G.S., and A. Pakes, 1996, The Dynamics of Productivity in the Telecommunications Equipment Industry, *Econometrica* 64, 1263-1297.

Pagano, M., and G. Pica, 2012, Finance and Employment, *Economic Policy* 27, 5-55.

Paravisini, D., V. Rappoport, P. Schnabl, and D. Wolfenzon, 2014, Dissecting the Effect of Credit Supply on Trade: Evidence from Matched Credit-Export Data, *Review of Economic Studies,* forthcoming.

Petersen, M. A., and R. Rajan, 1994, The Benefits of Lending Relationships: Evidence from Small Business Data, *Journal of Finance* 49, 3-37.

Petersen, M. A., and R. Rajan, 2002, Does Distance Still Matter? The Information Revolution in Small Business Lending, *Journal of Finance* 57, 2533-2570.

Petrin, A., and J. Levinsohn, 2012, Measuring Aggregate Productivity Growth Using Plant-Level Data, *RAND Journal of Economics* 43, 705-725.

Rajan, R. G., and L. Zingales, 1998, Financial Dependence and Growth, *American Economic Review* 88, 559-586.

Schumpeter, J. A., 1934, *The Theory of Economic Development* (Oxford University Press, London).

Wurgler, J., 2000, Financial Markets and the Allocation of Capital, *Journal of Financial Economics* 58, 187-214.

Table 1
State Banking Deregulation Dates

This table presents the dates of interstate and intrastate deregulation events used in our analysis. We follow Amel (1993) and Kroszner and Strahan (1999) in determining these dates. See Section 1.3 for more details.

State	*Intrastate* Deregulation Year	*Interstate* Deregulation Year
Alabama	1981	1987
Alaska	<1970	1982
Arizona	<1970	1986
Arkansas	1994	1989
California	<1970	1987
Colorado	1991	1988
Connecticut	1980	1983
Delaware	<1970	1988
DC	<1970	1985
Florida	1988	1985
Georgia	1983	1985
Hawaii	1986	>1993
Idaho	<1970	1985
Illinois	1988	1986
Indiana	1989	1986
Iowa	1997	1991
Kansas	1987	1992
Kentucky	1990	1984
Louisiana	1988	1987
Maine	1975	1978
Maryland	<1970	1985
Massachusetts	1984	1983
Michigan	1987	1986
Minnesota	1993	1986
Mississippi	1986	1988
Missouri	1990	1986
Montana	1990	1993
Nebraska	1985	1990
Nevada	<1970	1985
New Hampshire	1987	1987
New Jersey	1977	1986
New Mexico	1991	1989
New York	1976	1982
North Carolina	<1970	1985
North Dakota	1987	1991
Ohio	1979	1985
Oklahoma	1988	1987
Oregon	1985	1986
Pennsylvania	1982	1986
Rhode Island	<1970	1984
South Carolina	<1970	1986

South Dakota	<1970	1988
Tennessee	1985	1985
Texas	1988	1987
Utah	1981	1984
Vermont	1970	1988
Virginia	1978	1985
Washington	1985	1987
West Virginia	1987	1988
Wisconsin	1990	1987
Wyoming	1988	1987

Table 2

This table presents summary statistics on different variables and estimates used in the paper. Table A shows summary statistics for the main sample used in the paper. *Sales* is the only variable using information from the Census of Manufacturers and available only for a subset of sample years. Variable definitions are in Appendix C. Panel B reports the average values of the factor elasticities estimated using different production function specifications and methods. Panel C, D, and E report the within industry dispersion in the estimated marginal product of labor, marginal product of capital, and firm total factor productivity across these approaches, respectively.

Panel A: Summary Statistics

Variable	Mean	Std	Nobs
Employment Growth	0.0089	0.4621	2,287,100
Employment Share	0.0272	0.0834	2,287,100
Employment Share Growth	-0.0131	0.4570	2,287,100
Employment	22.28	46.23	2,287,100
Sales ($1K 1987)	1,648	4,533	397,700
Age	5.20	4.50	2,795,000
Exit	0.0685	0.2526	2,287,100
Entry	0.0819	0.2743	2,795,000
Intra_Deregulation	0.6215	0.4850	2,795,000
Inter_Deregulation	0.4139	0.4925	2,795,000

Panel B: Estimated Factor Elasticities

	Translog		Cobb-Douglas	
Factor	OP	LP	OP	LP
Capital	0.0848	0.1052	0.0491	0.0562
Labor	0.3717	0.3793	0.3264	0.3002
Materials	0.4023	0.4455	0.5021	0.6222

Panel C: Dispersion in MPL (within industry-state-year)

	OP	LP
Translog Specification	0.3722	0.3788
Cobb-Douglas Specification	0.5198	0.5198

Panel D: Dispersion in MPK (within industry-state-year)

	OP	LP
Translog Specification	0.4804	0.5472
Cobb-Douglas Specification	0.4581	0.4581

Panel E: Dispersion in TFP (within industry-state-year)

	OP	LP
Translog Specification	0.3253	0.2975
Cobb-Douglas Specification	0.3287	0.3088

Table 3
Credit Market Deregulation and the Sensitivity of Labor Reallocation to Marginal Products

This table presents results linking the sensitivity of labor reallocation to the marginal product of labor within an industry-state (*LRSens*) to credit market deregulation. Panels A and B report results from the estimation of equations (7) and (8), respectively. The dependent variable is the annual change in the log of the firm's industry-state employment share. For a given year *t*, this change in share is computed including only firms present in both year *t* and *t-1*. *MPL* is the log of the marginal product of labor, which can be based on a Translog or Cobb-Douglas production function, with parameters estimated using the OP or LP approaches (see text for more details). *Dereg* is an indicator that equals one if the state has passed banking deregulation (intrastate or interstate). The control variables in all regressions include the one-year lag of age, its squared value, as well as the interactions of both these variables with *Dereg*. Standard errors are heteroskedasticity robust and clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Panel C reports the percentage changes in *LRSens* implied by the effects in Panel B. These percentage changes are computed as the ratio of the effects in Panel B to the estimated value of *LRSens* in the subsample that has not passed deregulation.

Panel A: Initial Evidence

	Outcome: Change in Log of Employment Share							
	Intrastate Deregulation				Interstate Deregulation			
	Translog		Cobb-Douglas		Translog		Cobb-Douglas	
	OP	LP	OP	LP	OP	LP	OP	LP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MPL	0.0283***	0.0273***	0.0262***	0.0263***	0.0309***	0.0282***	0.0277***	0.0277***
	(0.0023)	(0.0027)	(0.0014)	(0.0014)	(0.0021)	(0.0026)	(0.0013)	(0.0013)
MPL × *Dereg*	0.0186***	0.0153***	0.0116***	0.0116***	0.0208***	0.0196***	0.0129***	0.0129***
	(0.0019)	(0.0022)	(0.0016)	(0.0016)	(0.0020)	(0.0021)	(0.0016)	(0.0016)
Nobs	2,287,100	2,287,100	2,287,100	2,287,100	2,287,100	2,287,100	2,287,100	2,287,100
R-square	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
State-Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Main Specification

	Outcome: Change in Log of Employment Share							
	Intrastate Deregulation				Interstate Deregulation			
	Translog		Cobb-Douglas		Translog		Cobb-Douglas	
	OP	LP	OP	LP	OP	LP	OP	LP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MPL × *Dereg*	0.0081***	0.0079***	0.0068***	0.0065***	0.0151***	0.0160***	0.0117***	0.0117***
	(0.0012)	(0.0012)	(0.0014)	(0.0015)	(0.0020)	(0.0022)	(0.0019)	(0.0020)
Nobs	2,287,100	2,287,100	2,287,100	2,287,100	2,287,100	2,287,100	2,287,100	2,287,100
R-square	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
State-Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE x MP	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE x MP	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Magnitude of Changes in Labor Reallocation - Main Specification

	Intrastate Dereg		Interstate Dereg	
	OP	LP	OP	LP
Percentage Change in *LRSens*	27.3%	26.8%	45.5%	49.4%

Table 4

Credit Market Deregulation and Potential Labor Reallocation Gains

This table presents results linking the potential gains from labor reallocation within an industry-state to credit market deregulation. The results are the output from the estimation of equation (9). Potential gains from labor reallocation are computed using equation (5) (see the text for more details). *Dereg* is an indicator that equals one if the state has passed banking deregulation (intrastate or interstate). Standard errors are heteroskedasticity robust and clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Outcome: Log of Potential Labor Reallocation Gains							
	Intrastate Deregulation				Interstate Deregulation			
	Translog		Cobb-Douglas		Translog		Cobb-Douglas	
	OP	LP	OP	LP	OP	LP	OP	LP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dereg	-0.030	-0.021	0.025	0.025	-0.083	-0.047	-0.085	-0.085
	(0.034)	(0.034)	(0.033)	(0.033)	(0.058)	(0.062)	(0.063)	(0.063)
Nobs	11,000	11,000	11,000	11,000	11,000	11,000	11,000	11,000
R-square	0.10	0.08	0.12	0.12	0.10	0.08	0.12	0.12
State-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5
Magnitude of Industry Productivity Gains from Increased Labor Reallocation

This table presents results quantifying the cumulative industry productivity gains implied by the changes in labor reallocation gains. These gains are additional percentage increases in value added due to the additional intensive margin reallocation of labor, and are estimated using equation (6) (see text for more details). Panel A reports the gains implied by the results in Tables 3 and 4. Panels B, C, and D estimate these same gains in different subsamples of industries. Panel B restricts the analysis to industries in the top tercile of estimated returns to scale with the OP approach. Panels C and D further restrict the sample from Panel B to industries in the top 50% and top 33% of potential labor reallocation gains prior to deregulation (percentiles computed within the sample from Panel B).

Panel A: All Industries

	Intrastate Deregulation		Interstate Deregulation	
	OP	LP	OP	LP
Industry Productivity Gain_1 (%VA)	0.85%	0.76%	1.56%	1.52%
Industry Productivity Gain_2 (%VA)	1.13%	1.02%	2.08%	2.02%

Panel B: Industries with Estimated Returns to Scale Close to One

	Intrastate Deregulation	Interstate Deregulation
	OP	OP
Industry Productivity Gain_1 (%VA)	0.63%	1.66%
Industry Productivity Gain_2 (%VA)	0.85%	2.21%

Panel C: Industries with High Potential Labor Reallocation Gains (Top 50%)

	Intrastate Deregulation	Interstate Deregulation
	OP	OP
Industry Productivity Gain_1 (%VA)	1.72%	3.27%
Industry Productivity Gain_2 (%VA)	2.30%	4.36%

Panel D: Industries with High Potential Labor Reallocation Gains (Top 33%)

	Intrastate Deregulation	Interstate Deregulation
	OP	OP
Industry Productivity Gain_1 (%VA)	3.55%	4.53%
Industry Productivity Gain_2 (%VA)	4.74%	6.04%

Table 6
Credit Market Deregulation and Reallocation Gains from All Factors
Industries with Estimated Returns to Scale Close to One

This table presents two sets of results using the sample of industries in the top tercile of estimated returns to scale with the OP approach. Panel A reports results linking the sensitivity of labor reallocation to firm tfp within an industry-state (*TFPSens*) to credit market deregulation. These results are the output from the estimation of equation (11). The dependent variable is the annual change in the log of the firm's industry-state employment share. For a given year *t*, this change in share is computed including only firms present in both year *t* and *t-1*. *TFP* is the log of firm total factor productivity, which can be based on a Translog or Cobb-Douglas production function, with parameters estimated using the OP approach (see text for more details). *Dereg* is an indicator that equals one if the state has passed banking deregulation (intrastate or interstate). The control variables in all regressions include the one-year lag of age, its squared value, as well as the interactions of both these variables with *Dereg*. Panel B reports the percentage changes in *TFPSens* implied by the effects in Panel A in an analogous way to Panel C of Table 3. Panel C presents results linking the potential gains from the reallocation of all factors within an industry-state to credit market deregulation. The results are the output from the estimation of equation (9), with potential gains from reallocation computed using equation (10) (see the text for more details). Standard errors are heteroskedasticity robust and clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Changes in the Sensitivity of Reallocation to Firm Productivity

	Outcome: Change in Log of Employment Share			
	Intrastate Deregulation		Interstate Deregulation	
	Translog OP	Cobb-Douglas OP	Translog OP	Cobb-Douglas OP
	(1)	(3)	(5)	(7)
TFP× Dereg	0.0067***	0.0108***	0.0185***	0.0263***
	(0.0014)	(0.0024)	(0.0023)	(0.0033)
Nobs	755,000	755,000	755,000	755,000
R-square	0.01	0.01	0.01	0.01
State-Industry-Year FE	Yes	Yes	Yes	Yes
State FE x TFP	Yes	Yes	Yes	Yes
Year FE x TFP	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Panel B: Magnitude of Changes in the Sensitivity of Reallocation to Firm Productivity

	Intrastate OP	Interstate OP
Percentage Change in *TFPSens*	17.8%	50.5%

Panel C: Changes in Potential Reallocation Gains

	Outcome: Log of Potential Reallocation Gains			
	Intrastate Deregulation		Interstate Deregulation	
	Translog	Cobb-Douglas	Translog	Cobb-Douglas
	OP	OP	OP	OP
	(1)	(3)	(5)	(7)
Dereg	-0.084	-0.026	-0.061	-0.043
	(0.054)	(0.044)	(0.107)	(0.086)
Nobs	7,700	7,700	7,700	7,700
R-square	0.04	0.03	0.04	0.03
State-Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 7

Magnitude of Industry Productivity Gains from Increased Overall Factor Reallocation

This table presents results quantifying the cumulative industry productivity gains implied by the reallocation gains of all factors. These gains are additional percentage increases in value added due to the additional intensive margin reallocation of all factors, and are estimated using equation (6) (see text for more details). The analysis is restricted to industries in the top tercile of estimated returns to scale with the OP approach. Panels B and C further restrict this sample to industries in the top 50% and top 33% of potential reallocation gains prior to deregulation (percentiles computed within the sample of industries with estimated returns to scale close to one).

Panel A: Industries with Estimated Returns to Scale Close to One		
	Intrastate Deregulation	Interstate Deregulation
	OP	OP
Industry Productivity Gain_1 (%VA)	1.41%	2.82%
Industry Productivity Gain_2 (%VA)	1.89%	3.76%

Panel B: Industries with High Potential Overall Reallocation Gains (Top 50%)		
	Intrastate Deregulation	Interstate Deregulation
	OP	OP
Industry Productivity Gain_1 (%VA)	3.46%	4.68%
Industry Productivity Gain_2 (%VA)	4.61%	6.24%

Panel C: Industries with High Potential Overall Reallocation Gains (Top 33%)		
	Intrastate Deregulation	Interstate Deregulation
	OP	OP
Industry Productivity Gain_1 (%VA)	4.43%	6.62%
Industry Productivity Gain_2 (%VA)	5.91%	8.83%

Table 8
Identification of Deregulation Effects

This table presents results addressing the identification of the effect of credit market deregulation on the sensitivity of labor reallocation to the marginal product of labor (*LRSens*). Panel A reports results addressing the robustness of the effects in Panel B of Table 3 (columns (5) and (6)). The results in columns (1) and (2) add the variable *Dereg (-1 to -5)*, as well as its interactions with *MPL* and age controls (see Table 3). *Dereg (-1 to -5)* is an indicator that equals one in the five years prior to state credit market deregulation. The results in columns (3) and (4) add region-year fixed effects as well as their interaction with *MPL*. Panel B reports results using a matching approach. We examine if the sensitivity of labor reallocation to the marginal product of labor differentially changed in treated industries, when compared to matched industries, around the time of their deregulation episode. See the text for more details. These results are the output from the estimation of equation (12). *Treated* is an indicator that equals one for industries in states that deregulate credit markets. *Post* is an indicator that equals one after credit market deregulation dates. *MPL* is the marginal product of labor. We also include interactions of age controls (see Table 3) with *Treated, Post*, and *Treated × Post*. Panel C reports results examining the trends in *LRSens* prior to deregulation across the treated and control groups in our matching analysis. These results are based on linear regressions linking *Change in Log of Employment Share* to *MPL × Control, MPL × Treated, MPL × Time × Control,* and *MPL × Time × Treated.* This analysis also includes analogous variables replacing MPL with age variables (see Table 3) as controls and is based on the six years prior to the deregulation events examined in Panel B. See the text for more details. Standard errors are heteroskedasticity robust and clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Robustness of Previous Results				
	Outcome: Change in Log of Employment Share			
	Interstate Deregulation - Translog Specification			
	OP	LP	OP	LP
	(1)	(2)	(3)	(4)
MPL × Dereg	0.0095**	0.0087**	0.0122***	0.0134***
	(0.0039)	(0.0038)	(0.0021)	(0.0022)
MPL × Dereg (-1 to -5)	-0.0025	-0.0031		
	(0.0021)	(0.0020)		
Nobs	2,287,100	2,287,100	2,287,100	2,287,100
R-square	0.01	0.01	0.01	0.01
State-Industry-Year FE	Yes	Yes	Yes	Yes
State FE x MP	Yes	Yes	Yes	Yes
Year FE x MP	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Region-Year FE x MP			Yes	Yes

Panel B: Results Using Matching Approach

	Outcome: Change in Log of Employment Share			
	Interstate Deregulation -Translog Specification			
	Sample 1		Sample 2	
	OP	LP	OP	LP
	(1)	(2)	(3)	(4)
MPL × Treated × Post	0.0227***	0.0160***	0.0217***	0.0159***
	(0.0064)	(0.0059)	(0.0065)	(0.0063)
Nobs	914,500	914,500	704,000	704,000
R-squared	0.01	0.01	0.01	0.01
State-Industry-Year-Episode FE	Yes	Yes	Yes	Yes

Panel C: Are There Diffential Trends in Treated Industries Prior to Deregulation?

	Outcome: Change in Log of Employment Share	
	Interstate Deregulation -Translog Specification	
	6-Year Window Prior to Deregulation	
	OP	LP
	(1)	(2)
MPL × Time × Control	0.0112***	0.0131***
	(0.0068)	(0.0067)
MPL × Time × Treated	0.0107***	0.0095***
	(0.0027)	(0.0027)
Difference (Treated - Control)	-0.0013	-0.0035
	(0.0055)	(0.0056)
Nobs	191,900	191,900
R-squared	0.01	0.01
State-Industry-Year-Episode FE	Yes	Yes

Table 9
Alternative Approaches to Estimate Production Functions

This table presents the results in Panels B and C of Table 3 and Panel A of Table 5 across additional approaches to estimate production functions. See the text for more details on different estimation approaches. Panel C reports the magnitudes of cumulative output gains divided by the same gains in Panel A of Table 5 (also for interstate deregulation). Standard errors are heteroskedasticity robust and clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Changes in Labor Reallocation Sensitivity

	Outcome: Change in Log of Employment Share					
	Interstate Deregulation					
	Translog Specification			Cobb-Douglas Specification		
	OP2	OLS	FE	OP2	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)
MPL × *Dereg*	0.0154***	0.0288***	0.0242***	0.0125***	0.0277***	0.0277***
	(0.0024)	(0.0022)	(0.0017)	(0.0023)	(0.0013)	(0.0013)
Nobs	1,929,900	2,287,100	2,287,100	1,929,900	2,287,100	2,287,100
R-square	0.01	0.01	0.01	0.01	0.01	0.01
State-Industry-Year	Yes	Yes	Yes	Yes	Yes	Yes
State FE x MP	Yes	Yes	Yes	Yes	Yes	Yes
Year FE x MP	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Magnitude of Changes in Labor Reallocation

	OP2	OLS	FE
Percentage Change in *LRSens*	53.2%	48.4%	48.7%

Panel C: Magnitude of Industry Productivity Gains - Relative to Benchmark Values

	OP2	OLS	FE
Industry Productivity Gain	1.10	1.08	1.23

Table 10
Results Using Value-Added Production Functions

This table presents the results in Panels B and C of Table 3 and Panel A of Table 5 using value-added production functions. Panel C reports the magnitudes of cumulative output gains divided by the same gains in Panel A of Table 5 (also for interstate deregulation). Standard errors are heteroskedasticity robust and clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Changes in Labor Reallocation Sensitivity

Outcome: Change in Log of Employment Share

Interstate Deregulation

	Translog Specification			Cobb-Douglas Specification		
	OP	OLS	FE	OP	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)
MPL × *Dereg*	0.0156***	0.0163***	0.0150***	0.0141***	0.0140***	0.0151***
	(0.0021)	(0.0019)	(0.0022)	(0.0018)	(0.0017)	(0.0019)
Nobs	2,287,100	2,287,100	2,287,100	2,287,100	2,287,100	2,287,100
R-square	0.01	0.01	0.01	0.01	0.01	0.01
State-Industry-Year	Yes	Yes	Yes	Yes	Yes	Yes
State FE x MP	Yes	Yes	Yes	Yes	Yes	Yes
Year FE x MP	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Magnitude of Changes in Labor Reallocation

	OP	OLS	FE
Percentage Change in *LRSens*	61.4%	69.9%	74.6%

Panel C: Magnitude of Industry Productivity Gains - Relative to Benchmark Values

	OP	OLS	FE
Industry Productivity Gain	1.39	1.34	1.22

Table 11
Results Controlling for Differences in Worker Skill

This table presents the results in Panels B and C of Table 3 and Panel A of Table 5 with additional controls for differences in worker skill across firms. In addition to age controls, we now also include the average wage of firms (*wage*) as controls in the estimation of (8). These additional control variables are the one-year lag of *wage*, its squared value, as well as the interactions of both these variables with *Dereg*. Panel C reports the magnitudes of cumulative output gains divided by the same gains in Panel A of Table 5 (also for interstate deregulation). Standard errors are heteroskedasticity robust and clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Changes in Labor Reallocation Sensitivity

	Outcome: Change in Log of Employment Share			
	Interstate Deregulation			
	Translog Specification		Cobb-Douglas Specification	
	OP	LP	OP	LP
	(1)	(2)	(3)	(4)
MPL × *Dereg*	0.0150***	0.0159***	0.0116***	0.0116***
	(0.0020)	(0.0022)	(0.0019)	(0.0020)
Nobs	2,287,100	2,287,100	2,287,100	2,287,100
R-square	0.01	0.01	0.01	0.01
State-Industry-Year F	Yes	Yes	Yes	Yes
State FE x MP	Yes	Yes	Yes	Yes
Year FE x MP	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Panel B: Magnitude of Changes in Labor Reallocation

	OP	LP
Percentage Change in *LRSens*	45.3%	49.1%

Panel C: Magnitude of Industry Productivity Gains - Relative to Benchmark Values

	OP	LP
Industry Productivity Gain	1.02	0.97

Table 12
Reallocation and Firm-Level Productivity Gains

This table combines previous estimates for the additional reallocation gains after credit market deregulation across all factors (Panel A of Table 7) with estimated effects of credit market deregulation on firm level tfp. These results are restricted to the sample of industries in the top tercile of estimated returns to scale with the OP approach. See the text for more details.

Interstate Deregulation - Industries with Estimated Returns to Scale Close to One	
	Industry Productivity Gain_1 (%VA)
	OP
Firm-Level Productivity Gains	1.05%
Reallocation Gains Across All Factors	2.82%
Total Gains (Intensive Margin)	3.87%
Percentage of Gains from Firm-Level Channel	27.1%
Percentage of Gains from Reallocation Channel	72.9%

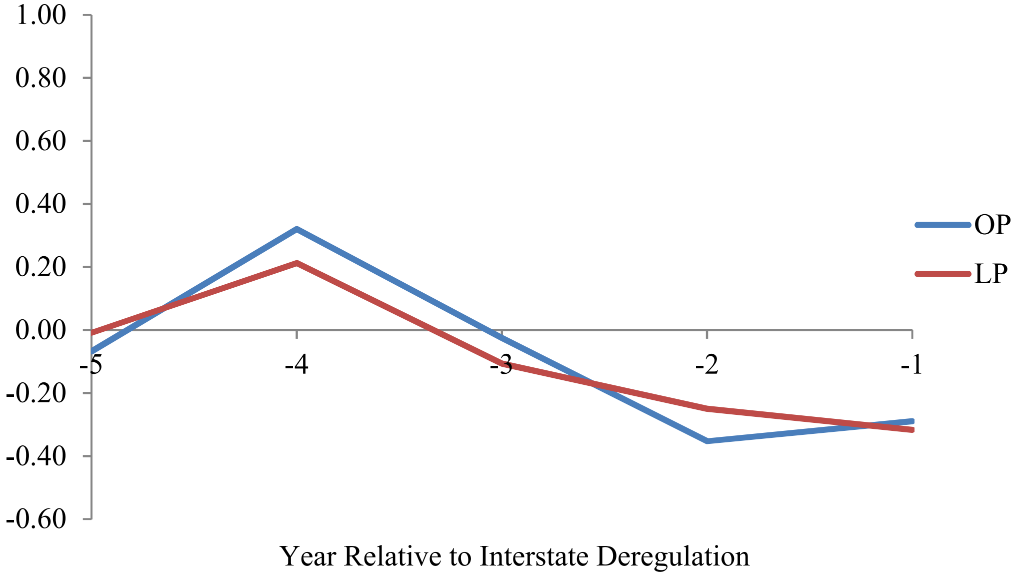
Figure 1

Differences in Labor Reallocation Prior to Interstate Deregulation

Change in Log of Employment Share Predicted by *MPL*

Normalized by Effects Estimated in Table 3

This figure presents results addressing the identification of the effect of credit market deregulation on the sensitivity of labor reallocation to the marginal product of labor (*LRSens*). The results break down by year the effect of *Dereg (-1 to -5) × MPL* reported in Panel A of Table 8 (columns (1) and (2)). These results are estimated by replacing *Dereg (-1 to -5)* with five separate indicator variables for each of the five years prior to deregulation. These five coefficients are normalized by the estimated effect of deregulation in Panel B of Table 3 (columns (5) and (6)).



Appendix A – Industry Productivity Decompositions

<u>Marginal Changes in Industry Productivity</u>

We first consider the case where industry output is given by $Y_{jt} = \sum_{i \in I_{jt}} Y_{ijt}$. Note that we can write equation (2) in the text as $Y_{jt} = \sum_{i \in I_{jt}} A_{ijt} F(SK_{ijt} \times K_{jt}, SL_{ijt} \times L_{jt}, SM_{ijt} \times M_{jt})$. The first-order condition for changes in Y_{jt} can therefore be written as:

$$\frac{dln(Y_{jt})}{dt} = \alpha_{jt} \frac{dln(K_{jt})}{dt} + \beta_{jt} \frac{dln(L_{jt})}{dt} + \gamma_{jt} \frac{dln(M_{jt})}{dt}$$
$$+ \sum_{i \in I_{jt}} \frac{dA_{ijt}}{dt} \frac{Y_{ijt}}{A_{ijt} Y_{jt}} + \sum_{i \in I_{jt}} \frac{\partial Y_{ijt}}{\partial L} \frac{L_{jt}}{Y_{jt}} \frac{dSL_{ijt}}{dt} \tag{A.1}$$
$$+ \sum_{i \in I_{jt}} \frac{\partial Y_{ijt}}{\partial K} \frac{K_{jt}}{Y_{jt}} \frac{dSK_{ijt}}{dt} + \sum_{i \in I_{jt}} \frac{\partial Y_{ijt}}{\partial M} \frac{M_{jt}}{Y_{jt}} \frac{dSM_{ijt}}{dt},$$

which leads to equation (4) in the text.

We now further decompose reallocation gains. For any factor F, note that $\sum_{i \in I_{jt}} \frac{dSF_{ijt}}{dt} = 0$. Therefore, we can write the factor's reallocation gains as $\frac{F_{jt}}{Y_{jt}} N_{jt} Cov\left(\frac{\partial Y_{ijt}}{\partial F}, \frac{dSF_{ijt}}{dt}\right)$, where N_{jt} is the number of firms in I_{jt}, and $Cov(.)$ denotes a covariance in the industry. Note that we can further rewrite these gains as $\frac{F_{jt}}{Y_{jt}} N_{jt} Var\left(\frac{\partial Y_{ijt}}{\partial F}\right) FRSensLevel_{jt}$, where $FRSensLevel_{jt} = \frac{Cov\left(\frac{\partial Y_{ijt}}{\partial F}, \frac{dSF_{ijt}}{dt}\right)}{Var\left(\frac{\partial Y_{ijt}}{\partial F}\right)}$. $FRSensLevel_{jt}$ is the additional increase in $\frac{dSF_{ijt}}{dt}$ predicted by a given increase in $\frac{\partial Y_{ijt}}{\partial L}$. More formally, is the coefficient on $\frac{\partial Y_{ijt}}{\partial F}$ in a linear regression within the industry of $\frac{dSL_{ijt}}{dt}$ on the previous variable and a constant. $FRSensLevel_{jt}$ can be approximated using a sensitivity in percentage terms. More formally, we can approximate $FRSensLevel_{jt} \approx FRSens_{jt} \times \frac{E(SL_{ijt})}{E(\frac{\partial Y_{ijt}}{\partial F})}$, where $FRSens_{jt} = \frac{Cov\left(MPF_{ijt}, \frac{\mathrm{dln}(SF_{ijt})}{dt}\right)}{Var(MPF_{ijt})}$ and $MPF_{ijt} = ln\left(\frac{\partial Y_{ijt}}{\partial F}\right)$. The approximation comes from the fact that we replace a regression coefficient in levels by one measured in logs adjusted based on the average value of the variables. $FRSens_{jt}$ can now be interpreted as the additional percentage change in factor shares (or factor growth) predicted by a given percentage difference in the marginal product of the factor. Since $E(SL_{ijt}) = \frac{1}{N_{jt}}$, we can approximate the factor's reallocation gains as $\frac{Var\left(\frac{\partial Y_{ijt}}{\partial F}\right)}{E\left(\frac{\partial Y_{ijt}}{\partial F}\right)} \frac{F_{jt}}{Y_{jt}} FRSens_{jt}$, what leads to equation (5) in the text. The potential gains from reallocating the factor are given by $\frac{Var\left(\frac{\partial Y_{ijt}}{\partial F}\right)}{E\left(\frac{\partial Y_{ijt}}{\partial F}\right)} \frac{F_{jt}}{Y_{jt}}$.

We then consider the case where industry output is given by $\frac{dln(Y_{jt})}{dt} = \sum_{i \in I_{jt}} \frac{Y_{ijt}}{Y_{jt}} \frac{dln(Q_{ijt})}{dt}$. Suppose that the real output production function of firms is given by:

$$Q_{ijt} = B_{ijt} H(K_{ijt}, L_{ijt}, M_{ijt}).$$

Then we can write

$$\frac{dln(Q_{ijt})}{dt} = \frac{dB_{ijt}}{dt} + \alpha_{ijt}^{0} \frac{dln(K_{ijt})}{dt} + \beta_{ijt}^{0} \frac{dln(L_{ijt})}{dt} + \gamma_{ijt}^{0} \frac{dln(M_{ijt})}{dt}, \qquad \text{(A.2)}$$

where α_{ijt}^{0}, β_{ijt}^{0} and γ_{ijt}^{0} denote the firm labor, capital, and materials real output elasticity, respectively. Note that, for any factor F, we can also write $\frac{dln(F_{ijt})}{dt} = \frac{dln(SF_{ijt})}{dt} + \frac{dln(F_{jt})}{dt}$. We can combine this result with (A.2) and rewrite industry output growth as:

$$\begin{aligned} \frac{dln(Y_{jt})}{dt} &= \alpha_{jt}^{0} \frac{dln(K_{jt})}{dt} + \beta_{jt}^{0} \frac{dln(L_{jt})}{dt} + \gamma_{jt}^{0} \frac{dln(M_{jt})}{dt} \\ &+ \sum_{i \in I_{jt}} \frac{\mathrm{dln}(B_{ijt})}{dt} \frac{Y_{ijt}}{Y_{jt}} + \sum_{i \in I_{jt}} \beta_{ijt}^{0} \frac{Y_{ijt}}{Y_{jt}} \frac{\mathrm{dln}(SL_{ijt})}{dt} \qquad \text{(A.3)} \\ &+ \sum_{i \in I_{jt}} \alpha_{ijt}^{0} \frac{Y_{ijt}}{Y_{jt}} \frac{dln(SK_{ijt})}{dt} + \sum_{i \in I_{jt}} \gamma_{ijt}^{0} \frac{Y_{ijt}}{Y_{jt}} \frac{\mathrm{dln}(SM_{ijt})}{dt}. \end{aligned}$$

The last three terms measure the additional industry output growth due to changes in factor shares and capture reallocation gains. For any factor F, note that the reallocation gain term in (A.3) can be written as $\sum_{i \in I_{jt}} P_{ijt} \frac{\partial Q_{ijt}}{\partial F} \frac{dSF_{ijt}}{dt} \frac{F_{jt}}{Y_{jt}}$. Intuitively, for any given factor F, reallocation gains are now evaluated by replacing $\frac{\partial Y_{ijt}}{\partial F}$ with $P_{ijt} \frac{\partial Q_{ijt}}{\partial F}$. Let ε_{ijt} denote the elasticity of demand for a firms' product. We have that $P_{ijt} \frac{\partial Q_{ijt}}{\partial F} = \frac{\partial Y_{ijt}}{\partial F} \left(\frac{\varepsilon_{ijt}}{\varepsilon_{ijt}-1} \right)$. For any factor F, we can therefore rewrite the reallocation gain term in (A.3) as $FRG_{jt}^{0} = \sum_{i \in I_{jt}} \left(\frac{\varepsilon_{ijt}}{\varepsilon_{ijt}-1} \right) \frac{\partial Y_{ijt}}{\partial F} \frac{dSF_{ijt}}{dt} \frac{F_{jt}}{Y_{jt}}$. If this elasticity is constant within an industry and given by ε_{jt}, then we can write that $FRG_{jt}^{0} = \left(\frac{\varepsilon_{jt}}{\varepsilon_{jt}-1} \right) FRG_{jt}$, where FRG_{jt} denotes the factor reallocation gains with our previous output measure. A further decomposition of reallocation gains analogous to our previous one will lead to the same value for $FRSens_{jt}$ as before and potential reallocation gains which are now given by $\left(\frac{\varepsilon_{jt}}{\varepsilon_{jt}-1} \right) \frac{Var\left(\frac{\partial Y_{ijt}}{\partial F} \right)}{E\left(\frac{\partial Y_{ijt}}{\partial F} \right)} \frac{F_{jt}}{Y_{jt}}$.

<u>Cumulative Changes in Industry Productivity</u>

Suppose we hold constant over time changes in an industry's total factors, firm-level productivity, as well as its firms' entry and exit decisions, including the output produced by firms in the first year they enter the industry. More specifically, we hold these conditions constant between years t and $t + \tau$. We also hold constant all industry conditions at year $t - 1$, including the initial allocation of factors. We then investigate the following question. How much higher is the output growth of the industry between years t and $t+\tau$ relative to a scenario with no resource reallocation over time? As in the marginal decomposition, this tells us the additional output growth due to changes in factor shares over time.

We denote the scenario we observe and the counterfactual with no reallocation as R and N, respectively. We denote $Y_{t+\tau}^{k}$ as the industry output produced in scenario k by firms that exist in the industry at year $t+\tau$. Note that the answer to our previous question is given by $\frac{Y_{t+\tau}^{R}-Y_{t+\tau}^{N}}{Y_{t+\tau}^{N}}$ and only depends on the output produced by the firms present in year $t+\tau$. We label these firms as final firms. We denote Y_{t+s}^{k} as the output produced in year $t+s$ by the final firms that already exist in the industry in that same year, and Y_{At+s}^{k} as the output produced in year $t+s$ by final firms also present in year $t+s-1$. Additionally, let Y_{Bt+s}^{R}=Y_{Bt+s}^{N} denote the output produced in year $t+s$ by final firms that entered the industry in year $t+s$.

Let g_{t+s}^{k} denote the growth between year $t+s$ and $t+s-1$ of the output produced by final firms present in both of these years. We have that $1+g_{t+s}^{D} \equiv (1+g_{t+s}^{R})/(1+g_{t+s}^{N})$ captures the additional growth of final firms in year $t+s$ due to intensive margin reallocation. Finally, let $s_{t+s}^{k} \equiv Y_{Bt+s}^{k}/Y_{t+s}^{k}$ denote the share of total output produced by final firms that comes from new entrants.

Given this notation, we can approximate our answer as:

$$\frac{Y_{t+\tau}^{R}-Y_{t+\tau}^{N}}{Y_{t+\tau}^{N}} \approx (1-s_{t+\tau}^{N})\, g_{t+\tau}^{D} + (1-s_{t+\tau}^{N})(1-s_{t+\tau-1}^{N})g_{t+\tau-1}^{D} + \cdots \qquad \text{(A.4)}$$

$$+(1-s_{t+\tau}^{N}) \ldots (1-s_{1}^{N})g_{1}^{D}.$$

This approximation comes from the fact that we are ignoring compounding. This approximation will be accurate for the magnitudes we consider in the paper. To show (A.4), note that we can write $\frac{Y_{t+s}^{R}-Y_{t+s}^{N}}{Y_{t+s}^{N}} = \left(\frac{Y_{At+s}^{R}-Y_{At+s}^{N}}{Y_{At+s}^{N}}\right)(1-s_{t+s}^{N})$ since $(1-s_{t+s}^{N}) = \frac{Y_{At+s}^{N}}{Y_{t+s}^{N}}$. Note now that we can approximate $\frac{Y_{At+s}^{R}-Y_{At+s}^{N}}{Y_{At+s}^{N}} \approx \frac{Y_{t+s-1}^{R}-Y_{t+s-1}^{N}}{Y_{t+s-1}^{N}} + g_{t+s}^{D}$. This approximation comes from the fact that $Y_{At+s}^{k} = Y_{t+s-1}^{k}(1+g_{t+s}^{k})$. This leads to $\frac{Y_{t+s}^{R}-Y_{t+s}^{N}}{Y_{t+s}^{N}} \approx (1-s_{t+s}^{N})g_{At+s}^{D} + \left(\frac{Y_{t+s-1}^{R}-Y_{t+s-1}^{N}}{Y_{t+s-1}^{N}}\right)(1-s_{t+s}^{N})$. If we iterate this step, we arrive at (A.4).

Intuitively, the terms g_{t+s}^{D} will capture marginal reallocation gains across final firms that exist in year $t+s$ and $t+s-1$. We can use a first-order approximation, as in our previous analysis, to analyze these marginal gains. As before, we can write each factor's reallocation gain as $\frac{F_{jt}}{Y_{jt}} N_{jt} Cov\left(\frac{\partial Y_{ijt}}{\partial F}, \frac{dSF_{ijt}}{dt}\right)$. However, these gains now need to be estimated using final firms' productivity at the end of the period, as opposed to their productivity at the time of reallocation, as we are interested in understanding how they affect their final industry output. Moreover, this first-order condition for g_{t+s}^{D} will capture a sum over only final firms that existed in the industry in years $t+s$ and $t+s-1$, as opposed to a sum across all industry firms that exist during that period.

Suppose now that current reallocation decisions are not correlated with future productivity shocks. To the extent that current reallocation is correlated with future productivity shocks, we will underestimate reallocation gains. Under this condition, we can write $g_{t+s}^{D} \approx RG_{t+s}^{F}\left(\frac{\theta}{1+\mu}\right)^{\tau-s}$ where RG_{t+s}^{F} is a first-order approximation to the reallocation gains of final firms computed with their productivity at the time of reallocation. Intuitively, θ captures the persistence of firm productivity and μ is the growth rate of firm-level productivity. In general, θ and μ can change by year. We have set them as constant for expositional simplicity. For any given factor F, let MPF_{t+s}^{1} and MPF_{t+s}^{2}denote the marginal product of the factor under the productivity in the reallocation period and the final period, respectively. Note that all other determinants of marginal products are fixed in this comparison. We can write $A_{it+\tau} = \theta^{\tau-s}A_{it+s} + \varepsilon_{it+\tau}$, where $E(\varepsilon_{it+\tau}) = 0$. If current reallocation decisions are uncorrelated with future productivity shocks then $Cov\left(MPF_{t+s}^{2}, \frac{d\ln(SF_{ijt})}{dt}\right) = Cov\left(MPF_{t+s}^{1}, \frac{d\ln(SF_{ijt})}{dt}\right)\left(\frac{\theta}{1+\mu}\right)^{\tau-s}$ since $Cov\left(\varepsilon_{it+\tau}, \frac{d\ln(SF_{ijt})}{dt}\right) = 0$. Let Y_{t+s}^{1} and Y_{t+s}^{2} denote the output of final firms under the productivity in the reallocation period and the final period, respectively. As before, all other determinants of final firms' output are fixed in this comparison. We have that $Y_{t+s}^{2} = (1+\mu)^{\tau-s}Y_{t+s}^{1}$. Together, these two conditions lead to $g_{t+s}^{D} \approx \frac{F_{jt}}{Y_{t+s}^{2}}N_{jt}Cov\left(MPF_{t+s}^{2}, \Delta SF_{ijt}\right) = \frac{F_{jt}}{Y_{t+s}^{1}}N_{jt}Cov\left(MPF_{t+s}^{1}, \Delta SF_{ijt}\right)\left(\frac{\theta}{1+\mu}\right)^{\tau-s} = RG_{t+s}^{F}\left(\frac{\theta}{1+\mu}\right)^{\tau-s}$.

Note that reallocation gains are computed as a percentage of output. An important condition we need for this analysis is that reallocation gains computed over the subset of final firms RG_{t+s}^{F} are similar to the ones computed across all firms in year $t+s$. This condition will hold if the dispersion of marginal products within final firms and within firms outside this subsample is significantly more important than the dispersion in marginal products across these two groups of firms. We have found that this is the case in our data. Under this condition, we can write:

$$\frac{Y_{t+\tau}^{R}-Y_{t+\tau}^{N}}{Y_{t+\tau}^{N}} \approx (1-s_{t+\tau}^{N})RG_{jt+\tau} + (1-s_{t+\tau}^{N})(1-s_{t+\tau-1}^{N})\left(\frac{\theta}{1+\mu}\right)RG_{jt+\tau-1} + \cdots \tag{A.5}$$

$$+(1-s_{t+\tau}^{N})\ldots(1-s_{1}^{N})\left(\frac{\theta}{1+\mu}\right)^{\tau-1}RG_{jt}.$$

This leads us to equation (6) in the text.

<u>Incorporating All Production Factors</u>

Under the assumptions discussed in Section 3.4, we can write our first measure of industry output as $Y_{jt} = A_{jt}H(K_{jt}, L_{jt}, M_{jt})$, where $A_{jt} = \sum_{i\in I_{jt}}\frac{L_{ijt}}{L_{jt}}A_{ijt}$ is a measure of industry productivity or total factor productivity. To see this, note that under these assumptions we have that $SL_{ijt} = SK_{ijt} = SM_{ijt}$ and can write $Y_{ijt} = \frac{L_{ijt}}{L_{jt}}A_{ijt}H(K_{jt}, L_{jt}, M_{jt})$, what leads to the previous result. This allows us to write the first-order condition for changes in Y_{jt} as:

$$\frac{dln(Y_{jt})}{dt} = \alpha_{jt}\frac{dln(K_{jt})}{dt} + \beta_{jt}\frac{dln(L_{jt})}{dt} + \gamma_{jt}\frac{dln(M_{jt})}{dt}$$

$$+\sum_{i\in I_{jt}} \frac{d\ln(A_{ijt})}{dt}\frac{Y_{ijt}}{Y_{jt}} + \frac{1}{A_{jt}}\sum_{i\in I_{jt}} A_{ijt}\frac{dSL_{ijt}}{dt}. \tag{A.6}$$

This gives us that $RG_{jt} = \frac{1}{A_{jt}}\sum_{i\in I_{jt}} A_{ijt}\frac{dSL_{ijt}}{dt}$.

Extensive versus Intensive Margin Effects

Under the previous conditions, we have a simple measure of industry productivity given by $A_{jt} = \sum_{i\in I_{jt}}\frac{L_{ijt}}{L_{jt}}A_{ijt}$. We will assume that these conditions hold in our analysis below. Once we have this simple measure of industry productivity, we can build on previous dynamic decompositions which isolate the contributions of resource reallocation in both the intensive and extensive margins to industry productivity growth (e.g., Foster, Haltiwanger, and Kriznan (2001)). More specifically, we can approximate annual changes in this measure as:

$$\frac{\Delta A_{jt}}{A_{jt-1}} = (1 - CShare_{jt})\left(\sum_{i\in C_{jt}}\frac{Y_{ijt}}{Y_{jt}}\Delta A_{ijt} + RG_{jt}\right) + Entry_{jt} + Exit_{jt}, \tag{A.7}$$

where $\Delta A_{jt} = A_{jt} - A_{jt-1}$, ΔA_{ijt} is defined analogously, C_{jt} denotes firms present in the industry in both year t and $t-1$, $CShare_{jt}$ denotes the share of C_{jt} in the industry's output in year $t-1$, RG_{jt} is a first-order approximation for our previous reallocation gains using annual data, and $Entry_{jt}$ and $Exit_{jt}$ capture the contribution of entry and exit to industry productivity growth, respectively.

To see this result, let A_{jt} denote the set of firms that enter the industry in year t and E_{jt} the set of firms that exit the industry after year t. We can write:

$$\Delta A_{jt} = \sum_{i\in C_{jt}} SL_{ijt}A_{ijt} - \sum_{i\in C_{jt}} SL_{ijt-1}A_{ijt-1} + \sum_{i\in A_{jt}} SL_{ijt}A_{ijt} - \sum_{i\in E_{jt-1}} SL_{ijt-1}A_{ijt-1}. \tag{A.8}$$

Note that $SL^C_{ijt} = \frac{SL_{ijt}}{\sum_{i\in C_{jt}} SL_{ijt}}$ gives us the shares allocated to firms that continue in the industry between year t and $t-1$ as a ratio of the total labor allocated to this group of firms. Note that industry marginal productivity growth in the intensive margin will be given by:

$$IPG^I_{jt} = \frac{\sum_{i\in C_{jt}} SL^C_{ijt}A_{ijt}}{\sum_{i\in C_{jt}} SL^C_{ijt-1}A_{ijt-1}} - 1.$$

The marginal changes in industry productivity we analyze in the paper will capture this effect. For any group $G_{jt} \in \{I_{jt}, C_{jt}, A_{jt}, B_{jt}\}$, let $A^G_{jt} = \frac{\sum_{i\in G_{jt}} A_{ijt}SL_{ijt}}{\sum_{i\in G_{jt}} SL_{ijt}}$ denote the average productivity of the group and $TSL^G_{jt} = \sum_{i\in G_{jt}} SL_{ijt}$ denote the total labor share of the group.

Using the previous notation, we can rewrite (A.8) as:

$$\frac{\Delta A_{jt}}{A_{jt-1}} = (1 - CShare_{jt})IPG^I_{jt} + TSL^A_{jt}\left(\frac{A^A_{jt} - A^C_{jt-1}}{A_{jt-1}}\right) - TSL^E_{jt-1}\left(\frac{A^E_{jt-1} - A^C_{jt-1}}{A_{jt-1}}\right). \tag{A.9}$$

This leads to (A.7) if we decompose IPG_{jt}^{I} using our previous analysis. Intuitively, the contribution of entry (exit) to industry productivity growth is determined by the product of the following two terms. First, the gap in firm tfp between firms entering (exiting) and C_{jt}. The contribution of entry (exit) will be positive only if this gap has the same (opposite) sign. Second, the level of entry (exit) will determine how much this gap contributes to productivity growth. These two terms can be directly analyzed in the data, what allows us to analyze how they change after deregulation.

In the Internet Appendix, we estimate changes in these contributions of entry and exit with a differences-in-difference specification. This framework allows us to analyze the relative importance of changes in extensive and intensive margin reallocation effects after deregulation. We can compare the intensive margin reallocation effects in the paper to these estimated changes in the contribution of entry and exit to industry productivity growth associated with deregulation.

Appendix B – Estimation of Production Functions

We follow the set up and assumptions discussed in Ackerberg, Benkard, Berry, and Pakes (2006, hereafter ABBP). We present here the main idea underlying each estimation approach and refer to ABBP for a more detailed discussion of the assumptions underlying these approaches. Across approaches, we explicitly address both simultaneity and selection biases involved in the estimation of the production function specified in (1). For expositional simplicity, we here focus on the Cobb-Douglas specification. The analysis with a Translog production function is implemented in an analogous way. We denote $x_{ijt} = log(X_{ijt})$. We rewrite the production function in (1) as:

$$y_{ijt} = \beta_0 + \beta_a age_{ijt} + \beta_k k_{ijt} + \beta_l l_{ijt} + \beta_m m_{ijt} + \omega_{ijt} + \epsilon_{ijt},$$

where ϵ_{ijt} is a shock revealed to firms at time t after all decisions have been made, age_{ijt} is the firm's age and ω_{ijt} is a productivity component observed by the firm before making decisions in year t. Note that firm tfp is given by $a_{ijt} = \beta_0 + \beta_a age_{ijt} + \omega_{ijt} + \epsilon_{ijt}$ and can be inferred as $y_{ijt} - \beta_k k_{ijt} - \beta_l l_{ijt} - \beta_m m_{ijt}$ if we know production function parameters.

<u>OP Approach</u>

Let i_{ijt} denote firm investment. A first important condition for this approach is that, conditional on the sample of firms with positive investment $i_{ijt} > 0$, we can write $\omega_{ijt} = h_t(age_{ijt}, k_{ijt}, i_{ijt})$. In other words, conditional on a firm's age and capital stock, firms' investment i_{ijt} allow us to uniquely determine ω_{ijt}. Moreover, conditional on all information available for firms at year t, ω_{ijt} is a sufficient statistic for predicting ω_{ijt+1}. A second important condition for this approach is that firms decide to operate in year t if and only if $\omega_{ijt} \geq \pi_t(age_{ijt}, k_{ijt})$. This means that the decision to operate is monotonic on ω_{ijt} and l_{ijt-1} and m_{ijt-1} are not state variables.

Let $\varphi_t(age_{ijt}, k_{ijt}, i_{ijt}) = h_t(age_{ijt}, k_{ijt}, i_{ijt}) + \beta_0 + \beta_a age_{ijt} + \beta_k k_{ijt}$.

In the first stage, we estimate $y_{ijt} = \varphi_t(age_{ijt}, k_{ijt}, i_{ijt}) + \beta_l l_{ijt} + \beta_m m_{ijt} + \epsilon_{ijt.}$ This allows us to estimate β_l and β_m, as well as obtain a fitted value for $\widehat{\varphi_{ijt}}$. We estimate this equation using a polynomial and on the sample with $i_{ijt} > 0$. Let X_{ijt} be an indicator that equals one of the firm decides to operate in year t and I_{ijt} denote the firms' entire information set at year t. Let $P_{ijt} = P(X_{ijt} = 1 | I_{ijt-1})$. In the second stage, we estimate a fitted value for P_{ijt}. Under the OP assumptions, we can write $P_{ijt} = P_t(age_{ijt-1}, k_{ijt-1}, i_{ijt-1})$ and estimate a fitted value $\widehat{P_{ijt}}$ for this expression using a probit model with a polynomial.

In the third stage, we estimate the following equation:

$$y_{ijt} - \beta_l l_{ijt} - \beta_m m_{ijt} = \beta_0 + \beta_a age_{ijt} + \beta_k k_{ijt}$$
$$+ g(\varphi_{ijt-1} - \beta_0 - \beta_a age_{ijt-1} - \beta_k k_{ijt-1}, P_{ijt}) + \delta_{ijt}.$$

Under the OP assumptions, we have that $E(\delta_{ijt} | I_{ijt-1}, X_{ijt} = 1) = 0$. We use the previous fitted values for $\widehat{\varphi_{ijt}}$ and $\widehat{P_{ijt}}$, and estimate β_0, β_a and β_k using non-linear least squares.

LP Approach

We now assume that, conditional on the sample of firms with positive investment $i_{ijt} > 0$, we can write $\omega_{ijt} = h_t(age_{ijt}, k_{ijt}, m_{ijt}, i_{ijt})$. Conditional on a firm's age and capital stock, now we need both firms' investment i_{ijt} and materials choice m_{ijt} to uniquely determine ω_{ijt}. We keep all other assumptions from OP, including the assumption that l_{ijt-1} and m_{ijt-1} are the only state variables. We term this approach as LP. In this approach, m_{ijt} provides additional information that might be important to construct a "proxy" for ω_{ijt}.

We can no longer identify the materials coefficient in the first stage. Following the discussion in ABBP we also assume that labor cannot be identified in the first stage and is also uniquely determined as $l_{ijt} = l_t(age_{ijt}, k_{ijt}, m_{ijt}, i_{ijt})$. They argue that is unlikely to be variation in l_{ijt} to identify first-stage effects once we have conditioned on these conditions that uniquely pin down firms' productivity.

We now define $\varphi_t(age_{ijt}, k_{ijt}, m_{ijt}, i_{ijt}) = h_t(age_{ijt}, k_{ijt}, m_{ijt}, i_{ijt}) + \beta_0 + \beta_a age_{ijt} + \beta_k k_{ijt} + \beta_m m_{ijt} + \beta_l l_{ijt}(age_{ijt}, k_{ijt}, m_{ijt}, i_{ijt})$.

In the first stage, we now estimate $y_{ijt} = \varphi_t(age_{ijt}, k_{ijt}, m_{ijt}, i_{ijt}) + \epsilon_{ijt.}$ In the second stage, we now have that $P_{ijt} = P_t(age_{ijt-1}, k_{ijt-1}, i_{ijt-1}, m_{ijt-1})$. As before, we obtain fitted values for $\widehat{\varphi_{ijt}}$ and $\widehat{P_{ijt}}$ in these two stages. We do not identify any factor elasticity in the first stage.

In the third stage, we now estimate:

$$y_{ijt} = \beta_0 + \beta_a age_{ijt} + \beta_k k_{ijt} + \beta_m m_{ijt} + \beta_l l_{ijt}$$
$$+ g(\varphi_{ijt-1} - \beta_0 - \beta_a age_{ijt-1} - \beta_k k_{ijt-1} - \beta_m m_{ijt-1} - \beta_l l_{ijt-1}, P_{ijt}) + \delta_{ijt}.$$

Under the LP assumptions, we still have that $E(\delta_{ijt} | I_{ijt-1}, X_{ijt} = 1) = 0$. However, we have that m_{ijt} and l_{ijt} potentially correlated with δ_{ijt}. We address this issue by using m_{ijt-1}, l_{ijt-1}, m_{ijt-2} and l_{ijt-2} as "instruments" for m_{ijt}, l_{ijt}, m_{ijt-1} and l_{ijt-1}. More precisely, we use these lagged variables when constructing moments conditions and use GMM.

<u>OP2 Approach</u>

We now assume that labor is a dynamic input, what allows us to explicitly incorporate adjustment costs in labor. We keep all other assumptions from OP. In this case, current labor decisions have dynamic implications and now we have that $\omega_{ijt} = h_t(age_{ijt}, k_{ijt}, i_{ijt}, l_{ijt})$ conditional on $i_{ijt} > 0$.

Similarly to labor in the previous case, we assume that materials cannot be identified in the first stage and is also uniquely determined as $m_{ijt} = m_t(age_{ijt}, k_{ijt}, l_{ijt}, i_{ijt})$. We now define $\varphi_t(age_{ijt}, k_{ijt}, l_{ijt}, i_{ijt}) = h_t(age_{ijt}, k_{ijt}, m_{ijt}, i_{ijt}) + \beta_0 + \beta_a age_{ijt} + \beta_k k_{ijt} + \beta_l l_{ijt} + \beta_m m_{ijt}(age_{ijt}, k_{ijt}, l_{ijt}, i_{ijt})$.

In the first stage, we now estimate $y_{ijt} = \varphi_t(age_{ijt}, k_{ijt}, l_{ijt}, i_{ijt}) + \epsilon_{ijt.}$ In the second stage, we now have that $P_{ijt} = P_t(age_{ijt-1}, k_{ijt-1}, i_{ijt-1}, l_{ijt-1})$. As in the LP case, we only obtain fitted values for $\widehat{\varphi_{ijt}}$ and $\widehat{P_{ijt}}$ in these two stages and do not identify any factor elasticity in the first stage.

In the third stage, we now estimate:

$$y_{ijt} = \beta_0 + \beta_a age_{ijt} + \beta_k k_{ijt} + \beta_m m_{ijt} + \beta_l l_{ijt}$$
$$+ g(\varphi_{ijt-1} - \beta_0 - \beta_a age_{ijt-1} - \beta_k k_{ijt-1} - \beta_m m_{ijt-1} - \beta_l l_{ijt-1}, P_{ijt}) + \delta_{ijt}.$$

As in the LP case, we use m_{ijt-1}, l_{ijt-1}, m_{ijt-2} and l_{ijt-2} as "instruments" for m_{ijt}, l_{ijt}, m_{ijt-1} and $l_{ijt-1}$when constructing moment conditions and use GMM.

Appendix C – Variable Definitions

As described in Section 2, our main data sources are the Longitudinal Business Database (LBD), the Census of Manufacturers (CM), and the Annual Survey of Manufacturers (ASM) from the U.S. Census Bureau. Across all variables, industries are defined as 3-digit SIC codes.

Employment – total firm employment from the LBD. Given our sample of single-plant firms, this is the same as total establishment employment.

Employment Growth - change in the log of firm employment between years t and $t-1$.

Employment Share – share of the industry-state employment.

Employment Share Growth – change in the log of the share of industry-state employment between years t and $t-1$. For any given year t, this variable is only defined for the sample of firms in the data in both years t and $t-1$. Total industry-state employment in both year t and year t-1 are computed only including these firms.

Sales – total value of shipments from the CM adjusted with industry deflator.

Age – firm age measured using the LBD.

Exit – indicator that equals one if the firm close its operations in the following year and constructed using the LBD.

Entry – indicator that equals one in the first year of the firm's operations and constructed using the LBD.

MPL – log of the estimated marginal product of labor. We first estimate production function parameters for each industry using the methods outlined in Appendix B. We then compute marginal products using the CM and estimated parameters. For any given year, this variable uses the estimated marginal product using data from the latest CM.

TFP – log of the estimated firm total factor productivity. We follow the same approach as in the construction of *MPL.*

Estimated Factor Elasticity – we first estimate the values of the factor elasticity across firms using data from the CM and estimated production function parameters. We then compute the average value of the estimated elasticity. This computation only includes CM observations.

MPL, MPK and TFP dispersion (within industry-state –year) – we first estimate the values of MPL, MPK and TFP using the CM and estimated production function parameters. We then compute the difference between each of these variables and their average value in their industry-state-year. Finally, we compute the standard deviation of these demeaned variables. This computation only includes CM observations.