Internet Appendix for

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

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This appendix contains three tables. Table IA.1 lists the dates of state banking deregulation events. Table IA.2 and IA.3 report the employment growth results and the financial policy results in the paper with alternative measures of firm productivity, respectively.

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1. Alternative Measures of Firm Total Factor Productivity

We consider alternative measures of firm total factor productivity, based on different methods to estimate the parameters of production functions. As described in Section 2, we estimate a Cobb-Douglas production function with separate parameters for each industry-year (3-digit SIC code). The production function parameters for an industry-year are estimated with plant-level data for the industry in the previous five years. Recall that firm and plant productivity are the same in our sample of single-plant firms. In the main measure used in the paper, these parameters are estimated with an OLS approach which includes year fixed effects. One potential concern with this approach is that unobservable differences in firm productivity could bias these estimates. This can happen because firm productivity will affect both firms' output and their input choices. Intuitively, to the extent that this issue matters for our results, it is likely that we will underestimate the economic significance of the effects of interest. In the presence of such measurement error, a given difference in measured firm TFP should predict a smaller gap in firms' actual TFP. This will lead us to estimate smaller sensitivities of outcomes with respect to firm TFP.

We now address this concern by considering two additional approaches to estimate plant-level production functions. In the fixed-effects approach, we add plant fixed effects to the previous OLS estimation. This ensures that the estimation of the previous coefficients is identified using only differential changes in the input choices of different plants over a same period of time. This approach will address the previous concern if unobservable differences in productivity across plants are fixed over time. However, this approach will not address the previous concern if differences in plant productivity change over time and these changes are correlated with shifts in firms' input choices.

In the model-based approach, we propose an estimation approach that builds on the model presented in Section 5 to address the previous concern. This approach is intuitive and provides accurate estimates for the production function coefficients in the context of this model. As in previous research analyzing plant- or firm-level productivity, we estimate production functions with industry-deflated sales as the outcome. In the context of the model of Section 5, we can denote firms' output as $Y_{ijt} = \frac{P_{ijt}Q_{ijt}}{D_{jt}}$, where D_{jt} is an industry deflator.Using the demand for differentiated products, we can write $Y_{ijt} = TFP_{ijt}K_{ijt}^{\widetilde{\alpha_J}}L_{ijt}^{\widetilde{\beta_J}}M_{ijt}^{\widetilde{\gamma_J}}$, where $TFP_{ijt} = C_{jt}A_{ijt}^{(\frac{\sigma-1}{\sigma})}$ captures our empirical measure of firm productivity, $C_{jt} = \frac{P_{jt}Q_{jt}^{1/\sigma}}{D_{jt}}$ is an industry-year constant, $\tilde{\alpha} = \alpha\left(\frac{\sigma-1}{\sigma}\right), \widetilde{\beta} = \beta\left(\frac{\sigma-1}{\sigma}\right)$, and $\tilde{\gamma} = \gamma(\frac{\sigma-1}{\sigma})$. Our analysis of firm production functions is based on the estimation of the following equation:

$$log(Y_{ijt}) = log(TFP_{ijt}) + \widetilde{\alpha_J}\times log(K_{ijt}) + \widetilde{\beta_J}\times log(L_{ijt}) + \widetilde{\gamma_J}\times log(M_{ijt}), \qquad \text{(IA.1)}$$

where $log(TFP_{ijt})$ is unobservable. Our measures of productivity are constructed using plant-level data and, as in our empirical results, we focus here on single-plant firms. This allows us to interpret (IA.1) as a plant-level production function. Recall that we include industry-year fixed effects in the estimation of (IA.1). We therefore estimate:

$$\Delta log(Y_{ijt}) = \Delta log(TFP_{ijt}) + \widetilde{\alpha_J}\times\Delta log(K_{ijt}) + \widetilde{\beta_J}\times\Delta log(L_{ijt}) + \widetilde{\gamma_J}\times\Delta log(M_{ijt}), \qquad \text{(IA.2)}$$

where ΔX_{ijt} is the difference between X_{ijt} and the average value of this variable in industry j and year t. The previous challenge for estimating these production-function parameters comes from the fact that the inputs will be correlated with $\Delta log(TFP_{ijt})$, which is unobservable before we estimated production-function parameters. In the context of the model in Section 5, we can address this issue by using the structure of the model to control for differences in $\Delta log(TFP_{ijt})$. Intuitively, we can use firms' choice of materials to control for potential gaps in productivity. In other words, in the context of our previous model, we can use these input decisions as a "proxy" for plant productivity along the lines of approaches used in industrial organization (e.g., Ackerberg, Benkard, Berry, and Pakes (2007)). Specifically, note that this model leads to a Cobb-Douglas revenue function given by:

$$R_{ijt} = D_{jt}TFP_{ijt}K_{ijt}^{\widetilde{\alpha_J}}L_{ijt}^{\widetilde{\beta_J}}M_{ijt}^{\widetilde{\gamma_J}}. \qquad \text{(IA.3)}$$

Recall that firms maximize their profits given by Equation (6). Given the revenue function in Equation (IA.3), the solution to firms' problem implies that ΔM_{ijt} is given by:

$$\Delta log(M_{ijt}) = \left(\frac{1}{1-\theta_j}\right)\left[\Delta log(TFP_{ijt}) - \widetilde{\beta_J}\times\Delta log(\widetilde{w_{ijt}}) - \widetilde{\alpha_J}\times\Delta log(\widetilde{R_{ijt}})\right] \qquad \text{(IA.4)}$$

where $\widetilde{w_{ijt}} \equiv w_{rt}(1+\tau_{Lit})$ and $\widetilde{R_{ijt}} = R_{rt}(1+\tau_{Kit})$ are measures of firms' marginal costs of using capital and labor (after distortions), respectively, and $\theta_j = \widetilde{\alpha_j} + \widetilde{\beta_j} + \widetilde{\gamma_j}$. We then assume that the distortions affecting these costs are determined by the following firm characteristics: age (*Age*), size (*Size*), productivity (*TFP*), and location (state). Our measure of size is an indicator for a broad size groups based on firm employment. In other words, we assume that we can write $\widetilde{w_{ijt}} = g^L_{jt}\left(Age_{ijt}, Size_{ijt}, TFP_{ijt}, r(i)\right)$ and $\widetilde{R_{ijt}} = g^K_{jt}\left(Age_{ijt}, Size_{ijt}, TFP_{ijt}, r(i)\right)$.

It is important to clarify why the previous assumption is consistent with the potential effect of financing constraints on both the capital and labor decisions of firms. These variables capture fundamental aspects of financing frictions. As long as differences in the importance of financing frictions are largely reflected in these variables, this assumption is plausible. Note that size and age are the two main firm characteristics associated with financing constraints. Also note that financing frictions could also depend on the cash flows of firms and this will be reflected inTFP_{ijt}. Another source of differences in the financing conditions faced by firms is local credit conditions and the region indicators will capture variation in these conditions. Based on this last assumption and Equation (IA.4), we can write that:

$$\Delta log\left(M_{ijt}\right) = f_{jt}\left(\Delta Age_{ijt}, \Delta Size_{ijt}, \Delta log\left(TFP_{ijt}\right), r(i)\right). \quad \text{(IA.5)}$$

Finally, we assume that the expression in (IA.5) monotonically increases with $\Delta log\left(TFP_{ijt}\right)$, conditional on the other firm characteristics (age, size, and location). This will be the case if the predicted change in $\widetilde{\beta_j} \times \Delta log\left(\widetilde{w_{ijt}}\right) + \widetilde{\alpha_j} \times \Delta log\left(\widetilde{R_{ijt}}\right)$ in response to an increase in $\Delta log\left(TFP_{ijt}\right)$ is positive and smaller than one. We found direct support for this last condition when we used values for $\Delta log\left(TFP_{ijt}\right)$ from our previous OLS approach. This condition is also empirically supported in analyses of misallocation and industry productivity (e.g., Hsieh and Klenow (2014)).

Under these assumptions, we can recover firms' productivity from their input (materials) decision conditional on the other firm characteristics. More precisely, we can write:

$$\Delta log\left(TFP_{ijt}\right) = h_{jt}\left(\Delta Age_{ijt}, \Delta Size_{ijt}, \Delta log\left(M_{ijt}\right), r(i)\right). \quad \text{(IA.6)}$$

Equation (IA.6) gives us an expression that we can use to control for differences in firm productivity while estimating Equation (IA.2). Notice that, if we control for $\Delta log\left(TFP_{ijt}\right)$, the estimation of Equation (IA.2) provides us with consistent estimators for the production function parameters. While we do not directly observe $\Delta log\left(TFP_{ijt}\right)$, condition (IA.6) determines this productivity as a function of observable variables.

For each industry and year, we estimate values for $\widetilde{\alpha_J}$, $\widetilde{\beta_J}$, and $\widetilde{\gamma_J}$ using (IA.2), (IA.6), and a simple iterative procedure. Our procedure uses an initial guess for the production function parameters and then searches for a fixed point using a feedback loop. We use as our initial guess the previous OLS estimates of (IA.2). We then use the following loop which has two steps. In the first step, we estimate predicted values for TFP_{ijt} using (IA.6). While we do not observe TFP_{ijt} we use our guess for production parameters and (IA.2) to compute $\Delta log\left(TFP_{ijt}\right)$. We assume that the unknown function h_{jt} is well behaved and model this function as a third-degree polynomial. In the second step, we use this predicted value for $TFP_{ijt}(\widehat{h_{Jt}})$ as a control in the estimation of (IA.2). This leads to new estimates for the production function parameters which we use as an updated guess in a new first step. We stop our procedure only when it leads to a fixed point.

As previously discussed, firms' choice of materials provides us with a "proxy" for firm productivity (conditional on certain firm characteristics) in this approach. This gives us a control for firm productivity which can then be used to adjust for differences in productivity while estimating production functions. While this approach is similar to methods used in industrial organization, it builds on the specifics of the model from Section 5 and takes into account the potential important role of financing frictions in shaping firms' choices of labor and capital.

2. Main Results with Alternative TFP Measures

We estimate our main results using the previous alternative measures of firm productivity. We focus on the robustness of our main growth and financial policy results. In each result, we only change the *TFP* measure being used and also compute *TFP* gaps to scale the effects using the specific *TFP* measure being analyzed. As in our previous results, all coefficients are multiplied by the average *TFP* gap between the top and bottom quartiles of an industry-state.

Table IA.2 presents this robustness in the context of the results from Table 2 (Columns (2) and (3) of Panel A). The estimated effects for *Dereg* × *TFP* × *Young1* remain economically and statistically similar. As in our previous results, deregulation is not associated with an increase in the relative growth of more productive firms in the sample of older firms. Table IA.3 presents the results from Table 5 (Columns (1) to (3) of Panel A) with alternative measures of firm TFP. The effect of deregulation on the link between *Bank Debt Share* and *TFP* remains economically similar and statistically significant among young firms. The pattern of this effect across age groups also remains similar. As in Table 5, this effect is statistically insignificant and economically much weaker for old firms. Overall, this analysis suggests that the previous concern with the estimation of firm TFP does not significantly affect our main results.

REFERENCES

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Table IA.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 1.1 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 IA.2
Banking Deregulation and Labor Reallocation: Alternative Firm TFP Measures

This table presents the results from Table 2 (Columns (2) and (3) of Panel A) with two alternative measures of firm *TFP*. These alternative measures are based on different methods to estimate the parameters of production functions. Production functions are based on a Cobb-Douglas specification with parameters that depend on each industry-year and are estimated with plant-level for the industry in the previous five years (see text for more details). Recall that firm and plant productivity are the same in our sample of single-plant firms. In the main measure used in the paper, these parameters are estimated with an OLS approach which includes year fixed effects. In the fixed-effects approach, we now add plant fixed effects to the previous OLS estimation. In the model-based approach, we implement a strategy to estimate these parameters that builds on the model presented in Section 5 of the paper (see text for details). All coefficients are multiplied by the average TFP gap between the top and bottom quartiles of an industry-state. In each result, these gaps are computed using the specific TFP measure being analyzed. The number of observations has been rounded to the nearest thousand following the Census Bureau's disclosure policy. Standard errors are heteroskedasticity robust and double clustered at the state and industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Outcome: Employment Growth			
	Fixed Effects Approach		Model-Based Approach	
	(1)	(2)	(3)	(4)
Dereg × TFP × Young1	0.0161***	0.0232***	0.0160***	0.0221***
	(0.0023)	(0.0026)	(0.0022)	(0.0025)
Dereg × TFP × Young2		0.0165***		0.0155***
		(0.0028)		(0.0030)
Dereg × TFP	0.0032	-0.0043*	0.0026	-0.0048**
	(0.0026)	(0.0025)	(0.0024)	(0.0023)
Year FE × TFP × Age Group	Yes	Yes	Yes	Yes
State FE × TFP × Age Group	Yes	Yes	Yes	Yes
Firm-Age Group FE	Yes	Yes	Yes	Yes
State-Industry-Year-Age Group FE	Yes	Yes	Yes	Yes
R-Square	0.07	0.07	0.07	0.07
Nobs	2,287,000	2,287,000	2,287,000	2,287,000

Table IA.3

Banking Deregulation and the Composition of Bank Lending: Alternative Firm TFP Measures

This table presents the results from Table 5 (Columns (1) to (3) of Panel A) with alternative measures of firm *TFP*. These alternative measures are based on different methods to estimate the parameters of production functions. Production functions are based on a Cobb-Douglas specification with parameters that depend on each industry-year and are estimated with plant-level for the industry in the previous five years (see text for more details). Recall that firm and plant productivity are the same in our sample of single-plant firms. In the main measure used in the paper, these parameters are estimated with an OLS approach which includes year fixed effects. In the fixed-effects approach, we now add plant fixed effects to the previous OLS estimation. In the model-based approach, we implement a strategy to estimate these parameters that builds on the model presented in Section 5 of the paper (see text for details). All coefficients are multiplied by the average TFP gap between the top and bottom quartiles of an industry-state. In each result, these gaps are computed using the specific TFP measure being analyzed. The number of observations has been rounded to the nearest thousand following the Census Bureau's disclosure policy. Standard errors are heteroskedasticity robust and double clustered at the state and industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Firm Fixed Effects Approach

	Outcome: Bank Debt Share		
	Young (Age 1-10)	Old (Age 11+)	Young (Age 1-5)
	(1)	(2)	(3)
Pre × IDereg × TFP	0.1927**	0.0263	0.2695**
	(0.0776)	(0.0383)	(0.1312)
State-Industry-Year FE	Yes	Yes	Yes
Pre × TFP Control	Yes	Yes	Yes
IDereg × TFP Control	Yes	Yes	Yes
R-Square	0.04	0.02	0.06
Nobs	4,000	10,000	2,000

Panel B: Model-Based Approach

	Outcome: Bank Debt Share		
	Young (Age 1-10)	Old (Age 11+)	Young (Age 1-5)
	(1)	(2)	(3)
Pre × IDereg × TFP	0.1937***	0.0318	0.2496***
	(0.0612)	(0.0386)	(0.0651)
State-Industry-Year FE	Yes	Yes	Yes
Pre × TFP Control	Yes	Yes	Yes
IDereg × TFP Control	Yes	Yes	Yes
R-Square	0.04	0.02	0.06
Nobs	4,000	10,000	2,000