The Great Cleansing*

Nadav Ben Zeev†
Ben-Gurion University of the Negev

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Abstract

This paper shows that the Great Depression, the worst economic downturn in U.S. history, was also a period associated with great cleansing, i.e., it was a period where aggregate total factor productivity (TFP) significantly increased through the relative rise in high-TFP establishments' activity at the expense of low-TFP ones. This novel cleansing evidence is obtained by applying a suitable estimation approach to an establishment-level dataset from the Census of Manufactures (COM) taken in 1929, 1931, 1933 and 1935, which produces a *loose* lower bound for the true aggregate cleansing effect. I find a significantly positive and persistent cleansing-induced rise in aggregate TFP. The baseline magnitude of this rise is 4.8-6.5 log points, supporting the view that the Great Depression was also a period of great cleansing and revealing a new and hitherto overlooked dimension of this period.

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Key words: Great Depression; Establishment-Level Total Factor Productivity; Cleansing Effect; Aggregate Total Factor Productivity; Production Function

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†*Contact details:* Department of Economics, Ben-Gurion University of the Negev. P.O.B 653, Beer-Sheva 84105, Israel.
Tel.: [+39] 055 4685 603, Fax: [+39] 055 4685 804
E-mail: nadavbz@bgu.ac.il.

1 Introduction

The Great Depression of 1929-1933 was the worst economic downturn in U.S. history with a 30% decline in real GDP and a peak unemployment rate of 25.4%. As shown in Figure 1, paralleling this dramatic downturn was also a considerable rise in a purified total factor productivity (TFP) measure that accounts for *inter*-industry input reallocation, increasing returns to scale, unobserved input utilization, and intermediate inputs. (This purified TFP series is from Watanabe (2016). See Page 28 for further discussion, details, and sources for this variable and its associated Figure 1.) This purified TFP measure grew by nearly 6% from 1929 to 1933 and increased further by an astounding rate of more than 28% from 1933 to 1935, leading to an overall growth rate for the 1929-1935 period of nearly 36%. Since aggregate TFP changes generally capture both an aggregate exogenous technology change as well as input-reallocation-induced changes, this striking rise in purified TFP constitutes meaningful motivation for studying the role of *intra*-industry input reallocation cleansing effects in the 1929-1935 period.

The 1929-1935 period, which is the only period from the first half of the 20th century for which the Census of Manufacturers' original establishment-level schedules managed to survive, covers both the downturn phase of the Great Depression as well as the early part of its recovery phase. As such, this period provides a rich setting for the formal examination of the extent of cleansing that can be associated with the Great Depression.

Terminology. The term 'TFP' throughout this paper refers to physical output per unit of composite input. Unless explicitly stated otherwise as 'revenue TFP' (i.e., nominal output per unit of composite input), 'TFP' pertains to physical TFP (i.e., physical output per unit of composite input).[1] Accordingly, the term 'aggregate TFP' represents the employment-weighted average of establishment-level TFP levels. (The terms 'employment' and 'labor' are also interchangeably used in this paper.)

[1] My econometric approach, by including location fixed effects, will arguably purge my estimated cleansing effect of horizontal-differentiation-induced differences in establishment-level prices. But vertical-differentiation-induced (i.e., quality-induced) price differences may still remain after this purging. Hence, although I do not explicitly model such quality-induced differences in my underlying framework (see Section 3), one can reasonably view my cleansing effect as arising from TFP differences across establishments that reflect both process innovation differences as well as product innovation differences.

The term 'micro-level cleansing effect' refers to the positive *causal* effect of initial TFP on future employment growth estimated from my establishment-level regressions; the term 'aggregate cleansing effect' delineates the rise in aggregate TFP which occurs due to a shift of labor from low-TFP establishments to high-TFP ones. Importantly, the labor shift underlying the aggregate cleansing effect structurally and conceptually builds on the micro-level cleansing effect which implies that high-TFP producers are predicted to grow more than low-TFP ones.

Objective. The objective of this paper is to study the extent of cleansing that took place during the Great Depression period, i.e., the extent to which aggregate TFP was increased by the shifting of resources from low-TFP producers to high-TFP ones. By using biennial establishment-level data from 1929 to 1935, I can illuminate the magnitude and the persistence of this cleansing mechanism for the Great Depression period.

To accomplish this objective, this paper unfolds in three parts. The first part lays out a simple underlying framework which serves as a conceptual base and guide for the empirical analysis that follows it. The second part consists of estimation of the establishment-level relation between initial TFP and subsequent employment growth (i.e., the micro-level cleansing effect). (For completeness, I also consider exit probability as an outcome variable.) And the third part quantifies this estimated micro-level effect's implications for aggregate TFP, i.e., it maps the micro-level cleansing effect into an aggregate cleansing effect. Both the latter parts' analysis is done in a suitable Bayesian estimation framework that facilitates straightforward inference and lower bound estimates for the true micro-level and aggregate cleansing effects.

The econometric model effectively includes three stages of estimation: estimation of establishment-level TFPs; estimation of micro-level cleansing effect; and estimation of aggregate cleansing effect, which is a highly nonlinear function of the micro-level cleansing effect. As such, this model renders it rather challenging to develop a classical inference procedure that accounts for an appropriate clustering of standard errors from each of the first two stages of estimation while also accounting for estimation uncertainty in all three stages. I therefore turn to a suitable Bayesian inference approach which serves as a convenient numerical procedure for an estimation that accounts for both the latter clustering and estimation uncertainty sought-after objectives, while all along using uninformative priors. (Appendix A analyzes the suitability of my estimation approach for identification of the true micro-level and aggregate cleansing effects while Appendix B provides the technical details of the estimation and inference procedure.)

Underlying Framework. This part lays out a simple conceptual framework, which underlies and guides this paper's empirical analysis, in two steps. First, it lays out a general setting of production and demand structure whose purpose is to produce a conceptual representation of nominal output, the outcome variable in the first of two stages of my micro-level cleansing effect estimation procedure. The latter representation underlies the examination of my estimation approach's suitability for identification of the true micro-level and aggregate cleansing effects and hence effectively guides this paper's entire empirical approach.

Second, it provides a standard definition of aggregate TFP and maps the estimated micro-level cleansing effect, which is estimated from the second part of the paper, into a cleansing-induced change in aggregate TFP (i.e., the aggregate cleansing effect). In standing on its underlying micro-level relation, this mapping's theoretical foundation lies in the prediction from canonical models of firm dynamics that producers with higher initial TFP are expected to see higher employment growth (see, e.g., Jovanovic (1982), Hopenhayn (1992), Hopenhayn and Rogerson (1993), and Ericson and Pakes (1995)).

Empirical Analysis: Micro-Level Cleansing Effect. This part estimates the effect of establishment-level TFP in 1929 on subsequent employment growth and exit probabilities from 1929 to 1931, 1933, and 1935, with all these future periods being considered separately in each of their corresponding regressions. The employment growth variable is considered separately for continuing establishments as well as for continuing and exiting establishments and, following Foster et al. (2016) and Decker et al. (2020), its response can be defined as the micro-level cleansing effect.

The estimation of this effect consists of two stages. The first estimates TFP as the residual from a regression of nominal output on labor and capital inputs as well industry and county fixed effects. And the second regresses future employment growth on the residual from the first stage.

(For completeness, I also consider exit probabilities as an outcome variable in this second stage.) As shown in Appendix A, my raw estimation procedure produces an upward biased micro-level cleansing effect estimate. Hence, I include in the estimation of the first stage a simple and theory-consistent bias-correction procedure which, as shown in Appendix A, produces a lower bound estimate of the true micro-level cleansing effect. As such, the estimated micro-level cleansing effect provides a conservative assessment of its true counterpart.

The results can be summarized as follows. Considering employment growth for both continuers and exiters, I find that having a logged TFP level that is one standard deviation higher than the industry average in 1929 leads to 7.5%, 5.9%, and 5.6% significantly higher employment growth in 1931, 1933, and 1935, respectively; considering only continuers, the effects are 9.1%, 5.9%, and 8.9%. And, considering exit probability as the outcome variable for completeness, higher initial TFP leads to a significant subsequent decline in exit probability of -1.3, -2.1, and -1.6 percentage points in 1931, 1933, and 1935, respectively. Underlying my micro-level cleansing results is a bias correction procedure which ensures that they constitute a lower bound for their true counterparts.

Empirical Analysis: Aggregate Cleansing Effect. This part studies the implications of the above-mentioned micro-level cleansing effect estimates for aggregate TFP. I first define aggregate TFP as the employment-weighted average of establishment-level TFPs. Then, following Foster et al. (2016) and Decker et al. (2020), I use the predicted employment weights based on the micro-level cleansing effect estimates (the entire sample based employment growth one as well as the continuers only sample based one) to compute the resultant aggregate TFP change in each of the three considered future years, while keeping the estimated TFP distribution fixed at 1929 levels. Comparing this counterfactual series to the base (1929) aggregate TFP level, I find a significant aggregate cleansing effect that amounts to 6.5, 5, and 4.8 log points in 1931, 1933, and 1935, respectively, for the continuers and exiters sample; and the corresponding numbers for the continuers only sample are 6.7, 4.1, and 6.3 log points.

Importantly, despite this paper's inherent data limitation that prevents an unbiased estimation of the TFP series (see discussion from Page 16), Appendix A.4.3 shows through a suitable simulation experiment that the above-reported estimated aggregate cleansing effects materially understate their true counterpart. This underestimation, under the most plausible calibration for the parameter governing inverse output demand elasticity, is in the order of the true aggregate cleansing effect being 39%-76% higher than its estimated counterpart. And, more generally, for essentially all values of this parameter the true aggregate cleansing effect is meaningfully higher than its estimated counterpart. Hence, the results for the aggregate cleansing effect can be interpreted as a *loose* lower bound of the true aggregate cleansing effect that took place in the Great Depression and are supportive of the notion that this period can also be considered as an episode of great cleansing.

Outline. The remainder of the paper is organized as follows. The next section provides a review of the relevant literature. Section 3 describes the underlying framework of this paper's empirical analysis. Section 4 provides a description of the data and methodology used in this paper. Section 5 presents the main results of this paper. Section 6 discusses the reconciliation of this paper's empirical results with the broader economy's aggregate TFP dynamics. The final section concludes.

2 Related Literature

This paper is closely related to the literature concerned with the behavior of productivity during the Great Depression. This literature can be divided into two strands. The first studies this behavior using aggregate or industry-level data. And the second tries to understand this behavior through the lens of establishment-level data.

Aggregate TFP in the Great Depression. Ohanian (2001) examines five potential drivers of the 18% decline in TFP during 1929-1933 (capacity utilization, quality of factor inputs, inter-sectoral misallocation,[2] labor-hoarding, and increasing returns to scale), finding that these factors explain together less than one-third of the latter 18% TFP decline. Field (2003) and Field (2006) treat the Great Depression more broadly as the 1929-1941 period, arguing that this decade saw

[2]It is noteworthy that, given the micro-level data I am using and my associated within-industry reallocation focused approach, this paper's cleansing effect finding is based on *intra-industry* reallocation (rather than inter-industry reallocation).

the most significant technological advancement of any comparable period in U.S. history. And Watanabe (2016) shows that the Great Depression's downturn can not be attributed to adverse technology shocks while its recovery was likely aided by favorable such shocks, obtaining this evidence by constructing an annual purified TFP series for 1892–1996 (covering the private non-farm sector) that controls for inter-industry input reallocation, varying input utilization, non-constant returns, and imperfect competition.[3]

Establishment-level Analysis of the Great Depression. This strand of the literature includes the works by Lee (2016) and Ziebarth (2020), which are the closest to my work in the literature. The former uses establishment-level data from six industries to examine the relation between 1929 productivity levels and employment growth and exit probabilities from 1929 to 1933 and finds weak evidence for a cleansing effect.[4] The latter uses the methodology from Hsieh and Klenow (2009) and a much richer micro-level dataset that covers 24 industries (which is also used in this paper, owing to the kind dissemination of this data by Chris Vickers and Nicolas Ziebarth),[5] which focuses on cross-sectional dispersion of establishment-level productivity (measured as value added labor productivity), and finds that changes in the establishment-level distribution of productivity were likely unimportant for understanding aggregate productivity from 1929-1935.

Relative to the work by Lee (2016), I am able to use a much larger baseline sample that is roughly 7.7 times larger than his baseline sample while also using a suitable Bayesian estimation framework which facilitates inference for the aggregate implications of the micro-level cleansing effect as well as the provision of lower bounds for both the micro-level and aggregate true cleansing effects. Both the latter aggregation procedure as well as my approach's informativeness about

[3]Similar to Watanabe (2016), Inklaar et al. (2011) also found that technology shocks were not the driving force behind the Great Depression's downturn while using a largely similar methodology but focusing only on the manufacturing sector and using biennial data covering 1919-1939.

[4]Lee (2016) uses value added labor productivity (nominal value added per labor input) as his first measure of productivity. The additional measure of productivity he uses is the residuals from an estimated Cobb Douglas production function consisting of labor and intermediate inputs.

[5]See Ziebarth (2015), Vickers and Ziebarth (2017), Vickers and Ziebarth (2018), and Benguria et al. (2020) for more details on this dataset. Relative to the dataset used by Lee (2016), my baseline sample is roughly 7.7 times larger than his. After removing establishments for which capital data is not available, the sample I am left with contains 20 industries.

the true counterparts of its estimated objects are absent from Lee (2016)'s analysis. This informativeness is crucial as it overcomes data limitations that prevent the proper measurement of physical/revenue TFP (see Page 16 for a discussion on these data limitations).

The difference between my analysis and that of Ziebarth (2020) is methodological and is rooted in our different conceptual frameworks. My underlying framework, which I use as a guide for my empirical framework, draws on the theoretical insight from canonical models of firm dynamics that producers with higher initial TFP are expected to see higher employment growth as well as lower exit probability (see, e.g., Jovanovic (1982), Hopenhayn (1992), Hopenhayn and Rogerson (1993), and Ericson and Pakes (1995)). This theoretical insight leads me to pursue a natural and appropriately modified application of the empirical approach used in Foster et al. (2016), Decker et al. (2020), and Blackwood et al. (2021), which focuses on micro-level regressions of subsequent employment growth on initial TFP, to the Great Depression time period available from Vickers and Ziebarth (2018)'s dataset. Ziebarth (2020) uses the theoretical framework from Hsieh and Klenow (2009) to guide his empirical analysis, which of course has its own merit and a slew of interesting findings but simply has a different focus than my analysis. In this sense, my work can be seen as complementary to that by Ziebarth (2020).

3 Underlying Framework

In what follows I lay out a simple conceptual framework which is meant to accomplish two objectives. The first, more general one, is to fix ideas and form a suitable conceptual base for this paper's entire empirical analysis. The second, specific to the third part of the paper that pursues a bottom-up estimation approach on the basis of the second part's estimated micro-level cleansing effect, is to provide a clear mapping between the latter micro-level effect and the aggregate cleansing effect which in turn operationalizes the third part of the paper. This mapping, in standing on its underlying micro-level relation, has its theoretical underpinning in the prediction from canonical models of firm dynamics that producers with higher initial TFP are expected to see higher future employment growth (see, e.g., Jovanovic (1982), Hopenhayn (1992), Hopenhayn and Rogerson (1993), and Ericson and Pakes (1995)).

3.1 General Conceptual Setting

There are I establishments indexed by i with $i = 1, 2, ..., I$. (For ease of exposition, and without loss of generality, I assume there is a single industry that contains these establishments.) Each establishment has nominal output, or revenue, $Y_{i,t} = P_{i,t}Z_{i,t}$ where $P_{i,t}$ and $Z_{i,t}$ are the price and quantity of establishment i's produced output, respectively.

Production Structure. I assume that physical intermediate inputs (i.e., materials, fuels, and electricity), denoted by $M_{i,t}$, enter the gross-output production function in a Leontief form such that

$$Z_{i,t} = \min(A_{i,t}L_{i,t}^{\alpha_L}K_{i,t}^{\alpha_K}, \vartheta_s M_{i,t}), \tag{1}$$

where $A_{i,t}$, $L_{i,t}$, and $K_{i,t}$ are establishment-level TFP and labor and physical capital inputs, respectively; α_L and α_K are the labor and capital production shares, assumed to be equal across establishments (which, as stated above, belong to the same industry); and ϑ represents the number of intermediate inputs required to produce one unit of gross output $Z_{i,t}$. This production structure has s long tradition in the literature (see, e.g., Burnside et al. (1995), Basu (1996), Gilchrist et al. (2013), Ackerberg et al. (2015), and Gandhi et al. (2020)) and has added merit in the context of manufacturing establishments whose conversion of intermediate inputs to outputs can be viewed as being based on some physical rule of fixed input-output proportionality with intermediate inputs having no substitutability in the production process.

Optimality requires that

$$Z_{i,t} = \vartheta M_{i,t} = A_{i,t}L_{i,t}^{\alpha_L}K_{i,t}^{\alpha_K}. \tag{2}$$

Output Demand Structure. Following Decker et al. (2020), I consider a simple demand structure with an establishment-level output demand function given by

$$P_{i,t} = e^{d_{i,t}}Z_{i,t}^{\psi-1}, \tag{3}$$

where $d_{i,t}$ is an idiosyncratic demand shock and $\psi - 1$ (with $\psi \leq 1$) is the inverse demand elasticity.[6]

This demand structure can be viewed as a standard horizontal product differentiation demand framework with $\psi = 1$ representing the case of no product differentiation. As such, it implies that the product differentiation embodied in Equation (3) can be reasonably interpreted as being rooted in within-industry spatial demand idiosyncracies. One possible extension of this demand structure is to allow for vertical-differentiation-induced price heterogeneity where higher prices reflect higher $A_{i,t}$ with the latter embodying product innovation (i.e., quality) in addition to process innovation. However, for ease of exposition, I refrain from modeling this intricate extension and suffice at pointing out here that my econometric approach only aspires to purge my estimated TFP series of horizontal-differentiation-induced price differences (i.e., those arising from spatial demand differences), leaving any vertical-differentiation-induced (i.e., quality-induced) price differences as attributable to the estimated cleansing effect.[7] This in turn renders a broader interpretation of this paper's estimated micro-level cleansing effect and its associated aggregate counterpart as being driven by both process and product innovation rather than just process innovation.

I now formalize the reasonable interpretation of $d_{i,t}$ as arising from spatial differentiation. Let the I establishments be dispersed geographically over C ($C < I$) locations such that each establishment operates in location c. This geographical dispersion is defined such that each location c ($c = 1, 2, ..., C$) is sufficiently small so that all establishments operating in that location have equal $d_{i,t}$'s. Hence, we can now equivalently denote $d_{i,t}$ by $d_{i,c(i),t}$ where $c(i)$ denotes the mapping between establishment i and location c and $d_{\varrho,c(\varrho),t} = d_{\varsigma,c(\varsigma),t}$ for all $\varrho, \varsigma \in c$ (i.e., $c(\varrho) = c(\varsigma)$). Hence,

[6] A more general demand formulation would also include aggregate output and price terms. However, as these are unimportant for my analysis, I abstract from them to ease exposition.

[7] As discussed in Foster et al. (2008)'s Section 3.3, such spatial demand differences essentially arise from consumers having different preference orderings over producers' locations. They also discuss the role of relationship capital between suppliers and consumers in generating these spatial demand differences, noting that relationship-induced demand differences are conceptually identical to those induced by regional variation as long as the contracts (explicit or implicit) borne out by this relationship capital reflect horizontal preference variation across consumers rather than vertical differentiation. This discussion is important for this paper's purposes as if these relationship-induced contracts reflect vertical product differentiation, then they will just get reflected in physical TFP differences which broadly capture product quality differences in addition to technical efficiency (process innovation) differences. And if they capture horizontal differentiation, then $d_{i,t}$ - which, as I argue above and in further detail in Section 4.2 and Appendix A, can be controlled for in my analysis - will embody them.

the demand structure from Equation (3) that is relevant to this paper is now given by

$$P_{i,t} = e^{d_{i,c(i),t}} Z_{i,t}^{\psi-1}, \tag{4}$$

where now $d_{i,c(i),t}$ replaces $d_{i,t}$. This conceptual representation of the demand shock motivates my inclusion of county-level fixed effects in the empirical analysis so as to control for $d_{i,c(i),t}$, which in turn facilitates the suitability of the identification of the cleansing effect.

Representation of Nominal Output. Since $Y_{i,t} = P_{i,t,Z} Z_{i,t}$, we can relate nominal output $Y_{i,t}$ to output price and labor and capital inputs as follows:

$$Y_{i,t} = P_{i,t} A_{i,t} L_{i,t}^{\alpha_L} K_{i,t}^{\alpha_K}. \tag{5}$$

Combining Equation (5) with Equation (4) yields the following structural expression for nominal output:

$$Y_{i,t} = e^{d_{i,c(i),t}} A_{i,t}^{\psi} L_{i,t}^{\alpha_L+\psi-1} K_{i,t}^{\alpha_K+\psi-1}. \tag{6}$$

The structural representation from Equation (6) will be useful in facilitating the examination of the suitability of my estimation framework that is done in Appendix A.

Definition of Aggregate TFP. The literature studying manufacturing establishments defines aggregate TFP as a weighted average of establishments' TFPs where the weights are defined on either an output, composite input, or employment basis, depending on the associated research's objective and data availability . (See Table 8.1 from Foster et al. (2001) for a good review of the types of aggregate TFP indices used in the literature. Foster et al. (2001) show that these activity-weighted indices are similar using output, composite input, or employment weights.) I follow the recent works by Foster et al. (2016) and Decker et al. (2020) and define the aggregate TFP index, denoted by a_t, as the following employment-weighted TFP index:

$$a_t \equiv \sum_{i=1}^{I} w_{i,t} a_{i,t}, \tag{7}$$

where $w_{i,t} = \frac{L_{i,t}}{L_t}$ is the employment share in aggregate employment of establishment i and $a_{i,t}$ is the log of establishment i's TFP ($A_{i,t}$) in deviation from industry mean.

3.2 Micro-Level and Aggregate Cleansing Effects

3.2.1 Micro-Level Cleansing Effect

Following Foster et al. (2016) and Decker et al. (2020), I define the micro-level cleansing effect as the effect of establishment-level initial TFP on establishment-level future employment growth: the larger this effect is, the more cleansing there is as resources are shifted from low-TFP establishments to high-TFP ones. This definition draws on the theoretical insight from canonical models of firm dynamics that producers with higher initial TFP are expected to see higher future employment growth (see, e.g., Jovanovic (1982), Hopenhayn (1992), Hopenhayn and Rogerson (1993), and Ericson and Pakes (1995)). To formally define the micro-level cleansing effect, a theory-consistent true specification for future employment growth is required; this is what I turn to next.

True Specification for Future Employment Growth. Appendix A lays out a quite generic dynamic labor demand framework which produces the following true specification for employment growth from period t to period $t+h$ (denoted by $g_{i,t,t+h}$, where $t = 1929$ and $h = 2, 4, 6$):

$$g_{i,t,t+h} = \beta_{1,h} a_{i,t} + \beta_{2,h} l_{i,t} + \beta_{3,h} k_{i,t} + \beta_{4,h} d_{i,c(i),t} + \epsilon_{i,t+h}, \tag{8}$$

where $a_{i,t}$, $l_{i,t}$, and $k_{i,t}$ are logs of establishment i's physical TFP, employment, and physical capital, respectively, with corresponding coefficients β_1, β_2, and β_3; and $d_{i,c(i),t}$ is the demand shock from Equation (6) with corresponding coefficient $\beta_{4,h}$, where $c = 1, 2, ..., C$ ($C < I$) represents a location comprising establishments whose demand shock is common owing to it being rooted in horizontal differentiation (also see the discussion from Page 9); and $\epsilon_{i,t+h}$ is an error term capturing period $t+h$ idiosyncratic shocks to input prices and is assumed to be uncorrelated with $a_{i,t}$, $l_{i,t}$, $k_{i,t}$, and $d_{i,c(i),t}$. (All variables are in terms of deviation from industry means.)

Definition of True Micro-Level Cleansing Effect. Given the true specification from Equation (8), the true micro-level cleansing effect is defined as $\beta_{1,h}$, i.e., the effect of initial logged TFP being different from its industry mean on future employment growth. Theory predicts this effect to be positive and the more positive this effect is the more cleansing is taking place as resources are being shifted from low-TFP producers to high-TFP ones.

3.2.2 Aggregate Cleansing Effect

The aggregate cleansing effect takes as input the micro-level cleansing effect in order to compute the cleansing-induced change in aggregate TFP. This section explains the mapping between the micro-level and aggregate cleansing effect objects.

Definition of Aggregate Cleansing Effect. The true aggregate cleansing effect, denoted by $\mathbb{C}$, is formulated as

$$\mathbb{C}_{t,t+h} = \sum_{i=1}^{I} \mathbb{E}_t\big(w_{i,t+h} \mid a_{i,t}\big)\, a_{i,t} - \sum_{i=1}^{I} w_{i,t} a_{i,t}, \tag{9}$$

where $t = 1929$ and $h = 2, 4, 6$; and $\mathbb{E}_t\big(w_{i,t+h} \mid a_{i,t}\big)$ represents establishment i's expected employment share at horizon $t+h$ conditional on initial logged TFP (in deviation from industry mean).

Explicit Expression for $\mathbb{E}_t\big(w_{i,t+h} \mid a_{i,t}\big)$. The explicit expression for this conditional expectation as a function of $a_{i,t}$ is based on the micro-level cleansing effect and the relation between $g_{i,t,t+h}$ and $w_{i,t+h}$. Specifically, it is obtained by combining $\mathbb{E}_t\big(g_{i,t,t+h} \mid a_{i,t}\big) = \beta_{1,h} a_{i,t}$ with the relation $w_{i,t+h} = \frac{L_{i,t}(1+g_{i,t,t+h})}{\sum_{i=1}^{I} L_{i,t}(1+g_{i,t,t+h})}$. (Optimal prediction $\mathbb{E}_t\big(g_{i,t,t+h} \mid a_{i,t}\big) = \beta_{1,h} a_{i,t}$ is obtained from applying the latter conditional expectations operator to the true specification from Equation (8).) This combination leads to the following expression for $\mathbb{E}_t\big(w_{i,t+h} \mid a_{i,t}\big)$:[8]

$$\mathbb{E}_t\big(w_{i,t+h} \mid a_{i,t}\big) = \frac{L_{i,t}\Big(1 + \mathbb{E}_t\big(g_{i,t,t+h} \mid a_{i,t}\big)\Big)}{\sum_{i=1}^{I} L_{i,t}\Big(1 + \mathbb{E}_t\big(g_{i,t,t+h} \mid a_{i,t}\big)\Big)}. \tag{10}$$

[8] Since $w_{i,t+h}$ is a nonlinear function of $g_{i,t,t+h}$, it is apriori unclear that Equation (10) is sufficiently precise. However, as discussed in Appendix A.4.1, the approximation error from Equation (10) is negligible.

Explicit Expression for $\mathbb{C}_{t,t+h}$. Given Equation (10), I am now in position to provide the explicit representation for $\mathbb{C}_{t,t+h}$:

$$\mathbb{C}_{t,t+h} = \sum_{i=1}^{I} \left\{ \frac{L_{i,t}(1+\beta_{1,h}a_{i,t})}{\sum_{i=1}^{I} L_{i,t}(1+\beta_{1,h}a_{i,t})} a_{i,t} \right\} - \sum_{i=1}^{I} w_{i,t}a_{i,t} = \tag{11}$$

$$\frac{\sum_{i=1}^{I} a_{i,t}L_{i,t} + \sum_{i=1}^{I} \beta_{1,h}a_{i,t}^2 L_{i,t}}{\sum_{i=1}^{I} L_{i,t} + \sum_{i=1}^{I} \beta_{1,h}a_{i,t}L_{i,t}} - \sum_{i=1}^{I} w_{i,t}a_{i,t} = \frac{\sum_{i=1}^{I} a_{i,t}L_{i,t} + \sum_{i=1}^{I} \beta_{1,h}a_{i,t}^2 L_{i,t}}{\sum_{i=1}^{I} L_{i,t} + \sum_{i=1}^{I} \beta_{1,h}a_{i,t}L_{i,t}} - \frac{\sum_{i=1}^{I} a_{i,t}L_{i,t}}{\sum_{i=1}^{I} L_{i,t}}.$$

The aggregate cleansing effect from Equation (11), taking as input the micro-level cleansing effect, essentially computes the cleansing-induced change in aggregate TFP and therefore constitutes the central object of study in this paper.

4 Methodology

This section elucidates the methodology used in the empirical analysis undertaken in this paper. I first describe the data used in my empirical analysis. Then, I provide details for the estimation used in the micro-level empirical approach after which I turn to presenting the estimation underlying the bottom-up empirical approach. Further technical details of my estimation approach are shown in Appendix B.

4.1 Data

The data I use is from Vickers and Ziebarth (2018) and is derived from the Census of Manufacturers (COM) for 1929, 1931, 1933, and 1935, the only four years from the first half of the 20th century for which COM's original establishment-level schedules managed to survive. The raw sample covers 24 industries whose total value of output, establishment count, and total wage bill amount to about 20%, 10%, and 20% of the corresponding values for the entire manufacturing sector.[9]

[9] Further details for this dataset are provided in Ziebarth (2015), Vickers and Ziebarth (2017), Ziebarth (2020), and Benguria et al. (2020). As argued in the latter paper, while this sample is not randomly chosen, it is nevertheless fairly representative of manufacturing as a whole. Specifically, industries that make up this sample are similar to those industries not included in it in terms of size as measured by employment and revenue, as well as revenue labor productivity.

As discussed at the end of this section, after cleaning the data for my purposes the final sample I am left with contains 20 industries with a total of 17,767 establishments. The list of these industries, along with descriptive statistics for each industry on establishment count, output value, employment, and revenue labor productivity (the ratio of nominal output to employment), is shown in Table 1. The total value of establishment count, output, and employment for this sample amount to 8.4%, 14.2%, and 12.2% of the corresponding values for the entire manufacturing sector.

I now discuss in detail the main establishment-level variables I use for the empirical analysis. The presence of these variables in my econometric analysis is motivated by the theoretical framework presented in Section 3.1 and further detailed in Appendix A.1.

Nominal Output. This variable represents the nominal value of products produced in 1929. As discussed in Footnote 7 from Ziebarth (2015), 1929 is actually the only year in which the COM asked respondents for the value of products *sold* that year rather than value of products *produced* that year. However, the quality check analysis from Ziebarth (2015) finds insignificant differences between industry totals from the 1929-1935 COM data and those from outside sources and, importantly, these small differences do not behave differently for 1929. Hence, it is likely the case that establishments simply ignored the different phrasing of the revenue question and continued to report production-based revenue, which warrants my production-based interpretation of COM's 1929 revenue data.

Moreover, while it is possible in principle to observe output quantities from the COM as the schedules also provide information on physical output,[10] there are two reasons for why it is preferable for the purposes of this paper to use nominal output rather than physical output. First, as noted by Ziebarth (2020), there is wider coverage for the nominal output value variable than for the physical output variable. Second, also noted by Ziebarth (2020), many establishments produce a number of different products thus making it not obvious how to define such establishments' real output levels.

[10]The specific digitized dataset I am using does not have information on physical output but such data has been used in Ziebarth (2013) who utilizes establishment-level physical output data for Mississippi to estimate the real effects of bank failures and in Vickers and Ziebarth (2021) who utilize physical output data to analyze Establishment-level unit prices between 1929 and 1935 for over 100 manufactured goods.

Employment. Employment (labor input) is measured by the log of number of wage earners, where the latter represents the year average from monthly values. As discussed in Ziebarth (2020), the COM distinguishes between wage earners and salaried employees, or roughly blue and white collar employees. As data for the latter group lacks for all years except 1935, I focus on wage earners for my measurement of labor input. As also discussed in Ziebarth (2020), establishments are also asked to report on monthly manhours in only a handful of industry-years. But these questions are mostly about things like 'average shift length' or 'normal number of hours worked per week.' In addition to being rather vaguely worded, these questions are not available in every year. Hence, I measure labor input with number of wage earners.

Physical Capital. While physical capital stock is not directly available in the COM, there is a reasonable proxy for it in the form of electric motors' installed horsepower (from both purchased and generated electricity). Such proxy for the measurement of physical capital has been commonly used in the literature studying historical manufacturing data (see, e.g., Allen (1977), Bresnahan and Raff (1991), Bertin et al. (1996), Inklaar et al. (2011), and Lee (2015)). This variable was only collected in the 1929 and 1935 COMs and for the year of interest (1929) it is available for 17,830 establishments, which is a moderately smaller sample size than the availability of the other variables in the analysis (20,046 establishments).

Gross Margin. As explained in Appendix A.1, my bias-corrected estimate of the micro-level cleansing effect requires a measure of gross margin. I obtain this measure from the COM as the ratio of nominal value added (the difference between nominal output value and nominal intermediate input costs (costs of raw materials, fuels, and purchased electric energy)) to nominal output value.

Employment Growth. I measure employment growth from period t to $t+h$ for establishment i as $g_{i,t,t+h} = \frac{L_{i,t+h}-L_{i,t}}{L_{i,t}}$. I generate this outcome measure for the entire sample (i.e., continuers and exiters sample) as well as the continuers only sample. Moreover, for completeness, I also consider an exit probability outcome variable which receives the value of one if establishment i

exited between period t and period $t+h$ and zero otherwise.[11]

Revenue Labor Productivity. Revenue labor productivity is measured as $\frac{Y_{i,t}}{L_{i,t}}$, i.e., the ratio of nominal output value to employment (number of wage earners). This variable is measured for 1929 and is used as the labor productivity variable in the descriptive analysis on the role of entry from Section 5.4.

Sample Size. After removing establishments with negative values for any one of the output value, employment, capital, and gross margin variables in 1929, as well as establishments missing in 1929 either one of these variables, the baseline sample I am left with contains a total of 17,767 establishments in 1929 with 11,297 of these continuing in 1931; 7,273 of these continuing in 1933; and 6,085 of these continuing in 1935. (As mentioned above when discussing the capital variable, this variable's sample availability effectively dictates that of the empirical analysis with 2,248 establishments getting removed due to their lack of capital data.[12])

Can TFP be Directly Measured/Estimated from COM Data? A remark is in order about this paper's *inability* to directly estimate or measure TFP (physical or revenue), thus resorting to a two-step econometric approach which ultimately produces lower bound estimates for the true micro-level and aggregate cleansing effects. There are two reasons for this inability. The first is the very short time dimension of the COM, which is made even shorter for production function estimation purposes due to capital data being available only for 1929 and 1935. And the second is the fact that capital data lacks a measure of capital costs.

The latter very short time dimension (effectively including only two observations over time of 6,085 continuers) prevents a suitable panel based production function estimation that is capable

[11] Results are similar when I follow the literature's standard practice, that began with Davis et al. (1996), and measure employment growth from period t to $t+h$ for establishment i as $g_{i,t,t+h} = \frac{L_{i,t+h}-L_{i,t}}{0.5(L_{i,t+h}+L_{i,t})}$. However, while the baseline employment growth measure produces a negligible approximation error when computing the conditional expectation of future employment share and associated aggregate cleansing effect (see Appendix A.4.1), I have found that this is no longer the case for the Davis et al. (1996) growth measure due to the much greater nonlinearity it induces in the employment share function.

[12] The capital data contains 63 more establishments than the baseline 17,767 establishment sample because county-level identifiers are missing for 63 establishments of the 17,830 establishments for which capital data is available.

of addressing input factor endogeneity issues using time series instruments as in Basu et al. (2006) or proxy variables as in Olley and Pakes (1996) and Levinsohn and Petrin (2003). And the lack of capital cost data prevents using cost shares to calibrate the factor elasticities of the production function. (Regardless of this technical inability to use cost shares for estimation, a material drawback of such approach is that it assumes no adjustment costs for the associated inputs, which is clearly at odds with the general dynamic labor demand model underlying this paper's empirical approach which assumes labor adjustment costs (see Appendix A.1 for such generic model). As noted in Syverson (2011), this issue can be somewhat alleviated by taking time averages of cost shares to try to smooth out the idiosyncratic adjustment-cost-driven element. However, this requires a sufficiently long time dimension that is lacking from my data.)

4.2 Micro-Level Econometric Framework

This econometric framework aims at estimating the effects of initial establishment-level TFP on subsequent employment growth and exit probabilities. Canonical models of firm dynamics generally predict that, conditional on firm size, exit is more likely for low-TFP establishments and that establishment growth is increasing in TFP (see, e.g., Jovanovic (1982), Hopenhayn (1992), Hopenhayn and Rogerson (1993), and Ericson and Pakes (1995)). Of particular interest to this econometric framework is the effect of initial TFP on future employment growth as this effect in turn constitutes the true micro-level cleansing effect ($\beta_{1,h}$ from Equation (8)).

Ideally, to estimate these effects, one would need to observe physical TFP and use it as an explanatory variable for the employment growth and exit outcome variables. Alternatively, as is done in most of the literature, one would estimate the combined effects of physical TFP shocks and output demand shocks on these variables by using revenue TFP as the explanatory variable for these outcome variables. Such alternative and common estimation approach would require interpreting the estimated effects as arising from both TFP and demand shocks.

Given the very low (biennial) frequency of my data and its associated short time dimension, which is further exacerbated by the lack of capital data for 1931 and 1933, it is beyond the capacity of this paper to properly and reliably estimate a revenue TFP measure (let alone a physical one given the absence of prices from the data). See Page 16 for a more detailed discussion on the inability of this paper to appropriately estimate physcial/revenue TFP which also touches on the issue of lacking capital cost data.

Instead, as explained in the remainder of this section, I take a different identification approach which concedes this paper's incapacity to consistently estimate the micro-level cleansing effect and consequently turn to develop a conservative estimation framework that can deliver a lower bound for the true micro-level cleansing effect. This is done with a two-stage estimation procedure where the first regression regresses nominal output on industry and county fixed effects, employment, and physical capital; and in the second stage the residual from this regression is then used as the explanatory variable in a regression with future employment growth and exit probabilities as the outcome variables. Granted, the first step regression clearly yields a biased TFP series; nevertheless, this bias has a specific nature which guides the incorporation of a simple theory-consistent bias correction into the raw estimation procedure, ultimately leading to a bias-corrected estimated micro-level cleansing effect that is downward biased. This in turn renders the estimation informative about the true micro-level cleansing effect by providing an estimate that is a lower bound for its true counterpart.

Specification. I estimate the following two-equation system:[13]

$$y_i = \gamma_{ind} + \gamma_{county} + \gamma_1 l_i + \gamma_2 k_i + u_i, \tag{12}$$

$$g_{i,h} = \gamma_{me,h} + \delta_h \hat{u}_i + v_{i,h}, \tag{13}$$

where y_i, l_i, and k_i are logs of nominal output, employment, and capital in 1929; γ_{ind} are industry fixed effects; γ_{county} are county fixed effects, which conceptually correspond to demand shock $d_{i,c(i),t}$ from Equation (6); and, in accordance with the structural representation of nominal output from Equation (6), u_i is a residual that conceptually corresponds to ψa_i and has standard deviation σ_1; $g_{i,h}$ is either employment growth for continuers and exiters, employment growth for continuers only, or exit dummy variable, with all three outcome variables measured from 1929 to $1929 + h$ ($h = 2, 4, 6$) for the i'th establishment; $\gamma_{me,h}$ are multi-establishment firm fixed effects, intended to

[13] Since $t = 1929$ and subsequent years are 1931, 1933, and 1935 (i.e., $h = 2, 4, 6$), I omit the time index from the estimated micro-level specification from System (12)-(13) for conciseness.

account for network effects in multi-establishment firms which appear to be important in the Great Depression (Loualiche et al. (2019)) and whose inclusion accords with my conceptual treatment of an establishment as an autonomous unit;[14] $\hat{u}_i$ is the estimated residual from Equation (12) with corresponding coefficient of interest δ_h; and $v_{i,h}$ is a residual capturing idiosyncratic input price shocks (see theoretical framework from Appendix A) with standard deviation $\sigma_{2,h}$.

For future reference, let the stacked $\mathbb{A} = [\gamma_{ind}, \gamma_{county}, \gamma_1, \gamma_2]'$ and $B_h = [\gamma_{me,h}, \delta_h]'$ matrices represent the coefficient matrices from Equations (12) and (13), respectively. Hence, the parameters of these two equations can be summarized by pairs $\mathbb{A}$ and σ_1 and B_h and $\sigma_{2,h}$, respectively.

Identification. δ_h is the coefficient of interest in System (12)-(13). The motivation for this system comes from Equation (6), which shows that nominal output is driven by the labor and capital input variables in Regression (12) as well as unobserved physical TFP and demand shock, where the former is raised to the power of ψ which is equal to one plus the inverse elasticity of output demand and the latter is controlled for by county-level fixed effects γ_{county}.

The discussion from Page 9 motivates the use of γ_{county} to control for demand shock $d_{i,c(i),t}$, where $c(i)$ represents the mapping between establishment i and location c with this location assumed to be sufficiently small such that the demand shock is equal across all establishments belonging to this location. The crux of this motivation lies in my treatment of the demand shock as representing horizontal differentiation with any additional unaccounted for price differences reflecting vertical-differentiation-induced differences (i.e., product quality differences). These unaccounted for quality-induced differences, which therefore get absorbed into my micro-level cleansing effect estimate, imply a broader interpretation of my results as capturing both process- and product-innovation-induced cleansing effects. There are a total of 1,992 counties over which the 17,767 establishments are dispersed in 1929, which is an arguably sufficiently large number of locations for capturing well horizontal-differentiation-induced demand differences.

As formally shown in Appendix A, the fact that the true model likely possesses imperfectly elastic output demand (i.e., $\psi < 1$) renders the OLS estimation of δ_h upward biased for the true

[14] There are a total of 1,031 such fixed effects for the specification that includes both continuers and exiters, i.e., there are 1,031 multi-establishment firms in the sample. (These firms own an average number of 17.2 establishments.)

effect of $a_{i,t}$ on $g_{i,t,t+h}$ (i.e., $\beta_{1,h}$ from Equation (8)).[15] Nevertheless, Appendix A.1 puts forward a theory-consistent bias correction procedure, amounting to multiplying the raw nominal output variable for each industry by the inverse of the industry-specific cross-sectional average of gross margin, which in turn produces a downward biased estimate of the true micro-level cleansing effect. As such, this estimate can be viewed as a lower bound for its true counterpart, thus allowing my econometric approach to produce conservative results that are in turn meaningfully informative about the true micro-level cleansing effect.

Estimation and Inference. To facilitate inference for the bottom-up estimation procedure (to be discussed in the next section), I estimate System (12)-(13) with a Bayesian estimation and inference procedure that assumes a diffuse normal-inverse Wishart prior distribution for the regressions' coefficients and residual variance. Bayesian inference is suitable for my setting because there are effectively three estimation stages in my model, with the first two corresponding to Equations (12) and (13) and the third concerning the estimation of the cleansing-induced change in aggregate TFP (to be discussed in the next section) which is in turn a highly nonlinear function of the estimated coefficient of interest from the micro-level regression (i.e., δ_h from Equation (13)). The Bayesian procedure I utilize in this paper is appealing because it can deal with the latter nonlinearity while also being able to conveniently integrate clustering of the standard errors at the industry level into the estimation of Equations (12) and (13); account for estimation uncertainty for these equations and for the estimation of the aggregate cleansing effect; and use uninformative priors all along.

To account for estimation uncertainty in $\hat{u}_i$, I perform a two-stage Bayesian estimation procedure. In the first stage, I compute $\hat{u}_i$ from Equation (12) conditional on a posterior draw of this equation's coefficients. Then, in the second stage of this procedure, I use this estimated $\hat{u}_i$ as an explanatory variable in Regression (13) from which the posterior draw of $\hat{\delta}_h$ (the estimate of δ_h) can be estimated. Doing this a sufficiently large number of times produces a posterior distribution for $\hat{\delta}_h$ that properly accounts for estimation uncertainty in $\hat{u}_i$.

[15] In the analysis that shows this result, which appears in Appendix A.2, I differentiate terminologically between the non-bias-corrected and bias-corrected estimation procedures. For ease of exposition here, I refrain from this notational extension and simply describe in words the simple bias-correction procedure.

To account for correlation of the error term within industries, I apply a correction to the standard errors within my Bayesian estimation procedure for both its stages that clusters them at the industry level. In doing so I follow the suggestion from Müller (2013) to increase estimation precision in the presence of a misspecified likelihood function (as in mine) by replacing the original posterior's covariance matrix with an appropriately modified one. Appendix B provides full technical details of my estimation and inference procedure.

One final remark is in order about the reason for doing this two-stage estimation procedure as opposed to estimating it via a single regression that simply regresses future employment growth on y_i, l_i, k_i, $\gamma_{ind,h}$, $\gamma_{county,h}$, and $\gamma_{me,h}$. While these two estimation approaches are asymptotically equivalent, the merit of the two-stage estimation procedure lies in its facilitation of appropriate inference for the bottom-up econometric approach which estimates the aggregate cleansing effect. In particular, this estimation procedure is able to explicitly account for uncertainty in the estimation of u_i which in turn serves as an important input for the estimation of the aggregate cleansing effect.

4.3 Bottom-Up Econometric Framework

The objective of this econometric framework is to estimate the aggregate cleansing effect, i.e., $\mathbb{C}_{t,t+h}$ from Equation (11). Since $t = 1929$ and subsequent years are 1931, 1933, and 1935 (i.e., $h = 2, 4, 6$), I will denote the estimate of $\mathbb{C}_{t,t+h}$ concisely by $\hat{\mathbb{C}}_h$. To obtain this estimate, for every posterior draw of δ_h from the estimation of System (12)-(13) that includes as outcome variable employment growth (either for continuers and exiters or continuers only), I compute $\hat{g}_{i,h} = \hat{\delta}_h \hat{u}_i$ and then use this predicted value to generate the predicted employment share in period $1929 + h$, i.e., $\hat{w}_{i,h} = \frac{L_i(1+\hat{g}_{i,h})}{\sum_{i=1}^{I} L_i(1+\hat{g}_{i,h})}$, where $\hat{w}_{i,h}$ is establishment i's predicted employment share for year $1929 + h$ and L_i is establishment i's employment in 1929. I then use these predicted employment share weights to compute the posterior draw of $\hat{\mathbb{C}}_h$ from the following expression:

$$\hat{\mathbb{C}}_h = \sum_{i=1}^{I} \left\{ \frac{L_i(1+\hat{\delta}_h \hat{u}_i)}{\sum_{i=1}^{I} L_i(1+\hat{\delta}_h \hat{u}_i)} \hat{u}_i \right\} - \sum_{i=1}^{I} w_i \hat{u}_i = \tag{14}$$

$$\frac{\sum_{i=1}^{I} \hat{u}_i L_i + \sum_{i=1}^{I} \hat{\delta}_h \hat{u}_i^2 L_i}{\sum_{i=1}^{I} L_i + \sum_{i=1}^{I} \hat{\delta}_h \hat{u}_i L_i} - \sum_{i=1}^{I} w_i a_i = \frac{\sum_{i=1}^{I} \hat{u}_i L_i + \sum_{i=1}^{I} \hat{\delta}_h \hat{u}_i^2 L_i}{\sum_{i=1}^{I} L_i + \sum_{i=1}^{I} \hat{\delta}_h \hat{u}_i L_i} - \frac{\sum_{i=1}^{I} \hat{u}_i L_i}{\sum_{i=1}^{I} L_i}.$$

I generate 1000 such posterior draws from which I am then able to estimate the median cleansing-induced aggregate TFP log point change along with the 95% posterior bands of this estimate. The same is done for the coefficient of interest from Equation (12) (δ_h). (Appendix B contains the specific details of the posterior simulator I use to obtain these estimates.) Importantly, Appendix A.4.3 shows through a suitable simulation experiment that $\hat{\mathbb{C}}_h$ underestimates $\mathbb{C}_{1929,1929+h}$. Under a plausible calibration for ψ, the parameter that governs the inverse output demand elasticity (see Equation (4)), this underestimation is in the order of the true aggregate cleansing effect being 39%-76% higher than its estimated counterpart. More generally, the true aggregate cleansing effect is meaningfully higher than its estimated counterpart for essentially all values of ψ.

That $\hat{\mathbb{C}}_h$ meaningfully underestimates its true counterpart implies that my aggregate cleansing effect estimate constitutes a conservative estimate for its true counterpart and, as such, it provides a *loose* lower bound for it. My econometric approach can therefore be interpreted as an estimation approach that concedes that it can not consistently estimate the true, sought after aggregate cleansing effect but this concession is accompanied by an econometric conservatism that can still produce an informative estimate for this effect by providing a lower bound for it.

5 Empirical Evidence

This section first presents the baseline empirical results from both the micro-level and bottom-up econometric frameworks. Then, it briefly discusses results from three robustness checks, deferring the detailed presentation of these results to Appendix C. Finally, the section ends with an analysis of the role of entry.

5.1 Baseline Evidence: Micro-Level Econometric Framework

The baseline results from estimation of Equation (13) appear in the first column of Figure 2, which shows the estimated median (solid line) and 95% posterior band (dashed lines) values for the effect of $\hat{u}_i$. In computing this effect I normalize $\hat{u}_i$ by its estimated standard error. Since $\hat{u}_i$ is an estimate of 1929 logged TFP,[16] normalizing it by its standard deviation implies that we should interpret its effect on this paper's three considered outcome variables as arising from being above the mean industry logged TFP by one standard deviation. These outcome variables are measured from 1929 to $1929 + h$, i.e., the first column of Figure 2 effectively shows the estimated median and 95% posterior band values for $\hat{\delta}_h$ (for $h = 2, 4, 6$) from Equation (13).

The effects are both statistically and economically significant at all of the three considered horizons. In particular, considering the entire sample (i.e., including both continuers and exiters), being above the mean industry logged TFP by one standard deviation implies having higher employment growth of 7.2, 5.9, and 5.6 percentage points for the two-, four-, and six-year horizons, respectively; considering just the continuers, i.e., conditional on survival, these estimates are also very meaningful at 9.1, 5.9, and 8.9 percentage points. Effects are also quite meaningful for exit probabilities as being above the mean industry logged TFP by one standard deviation implies a lower exit probability by -1.3, -2.1, and -1.6 percentage points in 1931, 1933, and 1935, respectively.

5.2 Baseline Evidence: Bottom-Up Econometric Framework

This section reports the results for $\hat{\mathbb{C}}_h$ from Equation (14), i.e., the cleansing-induced log point change in aggregate TFP. This aggregate cleansing effect will inform us about the implications of the micro-level cleansing effect reported in the previous section for aggregate TFP.

The baseline results from this estimation appear in the second column of Figure 2, which shows the estimated median (solid line) and 95% posterior band (dashed lines) values for $\hat{\mathbb{C}}_h$ for the entire sample (continuers and exiters) as well as only continuers. The estimated effects are very meaningful for both samples, implying large increases in aggregate TFP relative to 1929 aggregate TFP level: for the full sample, aggregate TFP rises by 6.5, 5, and 4.8 log points in 1931, 1933, and

[16] Note that $\hat{u}_i$ is already in deviation from industry mean given that Equation (12), from which it is estimated, includes industry fixed effects.

1935, respectively; and, for the only continuers sample, aggregate TFP rises by 6.7, 4.1, and 6.3 log points in 1931, 1933, and 1935, respectively. In addition to the considerable magnitude of these numbers, we also learn from them about the persistence of the estimated aggregate cleansing effect given that the 1935 effects are both statistically and economically significant.

5.3 Robustness Checks

Appendix C examines the robustness of the baseline results for $\hat{\delta}_h$ and $\hat{\mathbb{C}}_h$ along three dimensions. The first considers an alternative formulation of the production structure from Section 3.1 which removes the Leontief production structure assumption and allows the intermediate input factor to be substitutable for the other input factors. The second deals with the issue of cross-sectional variation in input utilization. And the third concerns the application of the two-way standard error clustering approach from Cameron et al. (2011) to my setting, extending my baseline one-way clustering at the industry level to also allow for error dependence within states (in addition to within industries). The results from these three robustness checks, presented in Appendix C, are very similar to the baseline ones, bolstering confidence in this paper's message about a meaningful aggregate cleansing effect for the Great Depression period at hand.

5.4 The Role of Entry

The analysis so far has abstracted from the role of entry in the cleansing-induced effect of the Great Depression's period at hand. One may be concerned that this paper's message about this cleansing effect is overstated in case entrants' TFP levels fall meaningfully below those of exiting establishments. This concern is based on the reasonable viewpoint that entrants are effectively the replacers of exiters, and therefore if the latter are pushed out by a downturn-induced cleansing mechanism but at the same time are replaced by less productive entrants then this would in turn overstate the magnitude of the latter mechanism.

Unfortunately, this paper's data does not allow for a consistent estimation of establishments' TFP (also see related discussion on Page 16). An equally relevant limitation of my data for the analysis of the role of entry is that physical capital data is missing from 1931 and 1933 and hence for those years it is not possible to obtain any reasonable TFP measure. Hence, in the analysis that follows, I provide direct evidence on the role of entry by using revenue labor productivity (RLP) as a proxy for TFP. Since the analysis of the role of entry is descriptive regardless of the TFP measurement issue, as opposed to the causal analysis done so far in the paper, my using RLP instead of TFP for the role of entry is less problematic than if I were to use it in my cleansing effect based causal analysis as a direct measure of TFP. And its use as a proxy for TFP receives support from the evidence from Foster et al. (2001, 2006) that within-industry relative RLP measures are strongly correlated with within-industry relative revenue TFP (which in turn was shown by Foster et al. (2008) to be strongly correlated with physical TFP).

Specification. To provide direct evidence on the possible role of entrants in overstating the message of this paper, I need knowledge about entrants' RLP levels relative to those of exiters. Toward this end, I study a sample that includes only entrants and exiters from 1929 to subsequent years and estimate the following linear probability regression:

$$D_{i,h} = \gamma_{ind,h} + \gamma_{county,h} + \gamma_{me,h} + \chi_h rlp_{i,h} + e_{i,h}, \tag{15}$$

where $D_{i,h}$ is a dummy variable that obtains one (zero) if the i'th establishment entered (exited) from 1929 to 1929 + h, with $h = 2, 4, 6$; $\gamma_{ind,h}$ are industry fixed effects; $\gamma_{county,h}$ are county fixed effects; $\gamma_{me,h}$ are multi-establishment firm fixed effects, intended as in the baseline case to account for network effects in multi-establishment firms which appear to be important in the Great Depression (Loualiche et al. (2019)); and $rlp_{i,t}$ is the deviation of the log of establishment i's 1929 revenue labor productivity level (measured as the log of nominal output per wage earner) from industry mean and normalized to have unit standard deviation, with χ_h being the coefficient of interest in the regression; and $e_{i,h}$ is the residual.

Since there is no meaningful way by which to convert labor and physical capital inputs of entering establishments (which are observed in period 1929 + h) into 1929 (the period in which exiting establishments' inputs are observed) levels, i.e., the two groups' input variables can not be made comparable, I refrain from adding to Regression (13) the labor and capital variables that were included in the baseline case. This issue of course begs the question of how entering establishments' RLP levels are converted to 1929 levels. I implement a simple solution for this issue, which can not be applied to the physical input variables, and simply multiply entering establishments' RLP levels by the ratio of the CPI in 1929 to the CPI in period $1929 + h$.[17] This normalization, which exploits the fact that measured establishment-level RLP is *nominal* output per worker, brings entering and exiting establishments' observed RLP levels into common grounds and thus facilitates a proper comparison between entering and exiting establishments' RLP levels.

Results. The results from estimation of Equation (15) appear in Figure 3 and show the median (solid line) and 95% posterior bands (dashed lines) of the estimated χ_h ($\hat{\chi}_h$) from Equation (15). An establishment whose logged RLP is one standard deviation above industry mean is 2.5 percentage points *less* likely to be an entrant from 1929 to 1931.[18] While establishment age is not available from the COM data, it is obvious that entering establishments from 1929 to 1931 are at most two years old. Hence, assuming exiting establishments are on average older than these entering establishments, this result possibly speaks to some form of costly entry where there is some delay until young establishments catch up the establishments they effectively replaced in the market place in terms of RLP.[19]

In accordance with this costly entry view, an establishment whose logged RLP is one standard deviation above industry mean are 0.9 and 0.7 percentage points *more* likely to be an entrant from 1929 to 1933 and from 1929 to 1935, respectively (the 0.7 estimate is only marginally significant). That is, making the reasonable assumption that this result reflects older establishments than the corresponding 1931 result, it appears that aging of entering establishments allows them to not only catch up exiting establishments in terms of RLP but also significantly surpass them. That the coefficient for 1935 is only marginally significant is consistent with the notion that, ultimately, entering establishments tend to converge to exiting establishments in terms of their RLP.

[17] CPI is taken as the annual average of monthly CPI values from the NBER Macrohistory Database. Before taking this average, I seasonally adjust the monthly CPI data with an X-13 seasonal adjustment procedure.

[18] There are a total of 11,502 exiting and entering establishments for 1929-1931, with 6,470 and 5,032 exiting and entering establishments, respectively; the corresponding numbers for 1929-1933 are 14,885, 10,530, and 4,335; and for 1929-1935 they are 20,148, 11,682, and 8,466.

[19] Results are similar using value added productivity (nominal value added per worker) instead of RLP.

Summary. In sum, while there is some level of *initially* counteracting entry mechanism for the cleansing mechanism, it fully reverses in the subsequent biennial periods and even becomes significantly enhancing for the 1929-1933 aggregate cleansing effect. However, it is noteworthy that both the 1929-1931 and 1929-1933 estimates do not bear quantitatively meaningful aggregate implications. To see this, take for example the -2.5 percentage point estimate for 1929-1931 and assume for simplicity that $\hat{\chi}_1 = -0.437$, where 43.7% is the unconditional probability of being an entrant in the 1929-1931 sample, corresponds to 1929-1931 entrants' logged RLPs all being one standard deviation below industry mean. (This is of course just one example of entrants' RLP distribution which would generate $\hat{\chi}_1 = -0.437$ but is chosen here for illustrative purposes owing to its simplicity.) I.e., the actual 1929-1931 $\hat{\chi}_1 = -0.025$ estimate can be interpreted as implying that 94.3% $(1 - \frac{0.025}{0.437})$ of entrants have logged RLPs equal to industry mean (with the industry of course including exiters) while *only* 5.7% of entrants have one standard deviation lower logged RLP than industry mean. In other words, both the 1929-1931 $\hat{\chi}_1 = -0.025$ and 1929-1933 $\hat{\chi}_1 = 0.009$ estimates essentially imply that only a small share of entrants exhibits RLP differences with respect to exiters; the bulk of the RLP distributions for these two groups exhibits similar RLPs.[20]

Hence, considering the above-explained limited quantitative importance of the $\hat{\chi}_1 = -0.025$ estimate, the results from this section do not seem to imply that the message of this paper is overstated because of a counteracting entry-induced mechanism. The vast majority of entrants' and exiters' RLP distribution is similar and hence a meaningful role for either a counteracting or enhancing entry-induced mechanism can be effectively ruled out.

6 Reconciliation of Results with Aggregate TFP Dynamics

This paper estimates a cleansing-induced change in aggregate TFP in the order of 3.6-5.1 log points for the 1929-1935 period. Since aggregate TFP changes generally capture both an aggregate exogenous technology change as well as input-reallocation-induced changes, it is important to discuss this paper's results in the context of the broader economy's aggregate TFP behavior from the 1929-

[20]Doing the exercise above for $\hat{\chi}_1 = 0.009$ implies that the latter estimate can be interpreted as implying that 97.9% of entrants have logged RLPs equal to industry mean (with the industry of course including exiters) while *only* 2.1% of entrants have one standard deviation higher logged RLP than industry mean.

1935 period. Toward this end, this section examines this paper's significant aggregate cleansing effect through the lens of the behavior of two TFP measures for the non-farm private sector constructed from Kendrick (1961, 1973)'s interwar data, as reported in Watanabe (2016). The first measure is Kendrick (1961, 1973)'s own TFP measure which is a standard Solow residual while the second measure is Watanabe (2016)'s purified TFP measure which adjusts for increasing returns to scale, unobserved input utilization, and intermediate inputs.

Kendrick (1961, 1973)'s TFP Measure. This TFP measure declined by more than 10% during 1929-1933 but then increased by more than 15% over the period of 1933-1935 to stand at a roughly 5% higher level in 1935 relative to 1929. While the 1933-1935 TFP increase is easy to reconcile with this paper's results, the 1929-1933 decline in this TFP measure is hard to reconcile with the considerable aggregate cleansing effect found in this paper for this period.

But the pioneering work from Basu et al. (2006), which emphasized the importance of purging raw TFP measures of utilization- and nonconstant-returns-induced changes, suggests that Kendrick (1961, 1973)'s TFP measure likely captures additional factors such as input utilization and nonconstant returns to scale above and beyond the variation from aggregate exogenous technology and input-reallocation-induced changes. This is precisely the motivation for Watanabe (2016)'s desire to account for these biasing elements when constructing his aggregate purified TFP measure, which I turn to discuss next.

Watanabe (2016)'s TFP Measure. Following Basu et al. (2006)'s methodology, Watanabe (2016) constructs a purified TFP measure which differs from Kendrick (1961, 1973)'s TFP measure in that it accounts for *inter*-industry input reallocation, increasing returns to scale, unobserved input utilization, and intermediate inputs.[21] The behavior of this series over its associated sample of 1891-1966 is depicted in Figure 1, already referred to at the start of this paper.[22] This purified TFP measure grew by nearly 6% from 1929 to 1933 and increased further by an astounding rate of more than 28% from 1933 to 1935, leading to an overall growth rate for the 1929-1935 period

[21] Also see Huo et al. (2020) for the importance of properly controlling for unobserved input utilization for TFP measurement in an international context.

[22] I thank Shingo Watanabe for kindly sharing with me his purified TFP data.

of nearly 36%.[23] This dramatic increase in purified TFP over the 1929-1935 period, while likely also driven by technological advances, is still broadly consistent with the view that a considerable aggregate cleansing effect - coming from favorable *intra*-industry input reallocation - took place during this period.

Summary. Both TFP measures considered in this section, while accounting for inter-industry input reallocation changes via aggregation from industry-level TFP measures, do not account for intra-industry input reallocation changes. These changes, in turn, are precisely what this paper focuses on and estimates. While I acknowledge that technological advance also likely contributed to the considerable rise in Watanabe (2016)'s purified TFP measure over the 1929-1935 period, the fact that this measure does not account for intra-industry reallocation effects sits reasonably well with the intra-industry cleansing-induced effect I estimate in this paper.

7 Conclusion

This paper has provided robust evidence on a significant and persistent aggregate cleansing effect for the Great Depression (1929-1935) period. To obtain this evidence, I used a suitable micro-level data based econometric framework whose estimated aggregate cleansing effect is a *loose* lower bound for its true counterpart. My results deliver a baseline cleansing-induced effect on aggregate TFP of 5.1, 3.6, and 3.8 log points in 1931, 1933, and 1935, respectively. These material cleansing estimates reveal a new and hitherto overlooked dimension of the Great Depression period.

While data limitations prevent me from comparing the cleansing effects from 1929 establishment-level TFPs to those from other base years, this paper's considerable estimated aggregate cleansing effects have potentially meaningful policy implications given that policy intervention is often though of as having been lackluster for this period. In particular, while beyond the scope of this paper, studying the role of policy intervention (or lack thereof) in the Great Depression in shaping this paper's cleansing evidence constitutes an interesting avenue of future research. Such line of research can contribute to our understanding of the fundamental

[23] The average annual growth rate of purified TFP over the entire sample (1891-1966) is 2%. When excluding the 1929-1935 period, this number drops by 20% to 1.6%.

issue of whether policies directed at reducing the short-term severity of large downturns may at the same time also hinder the type of cleansing effects found in this paper.

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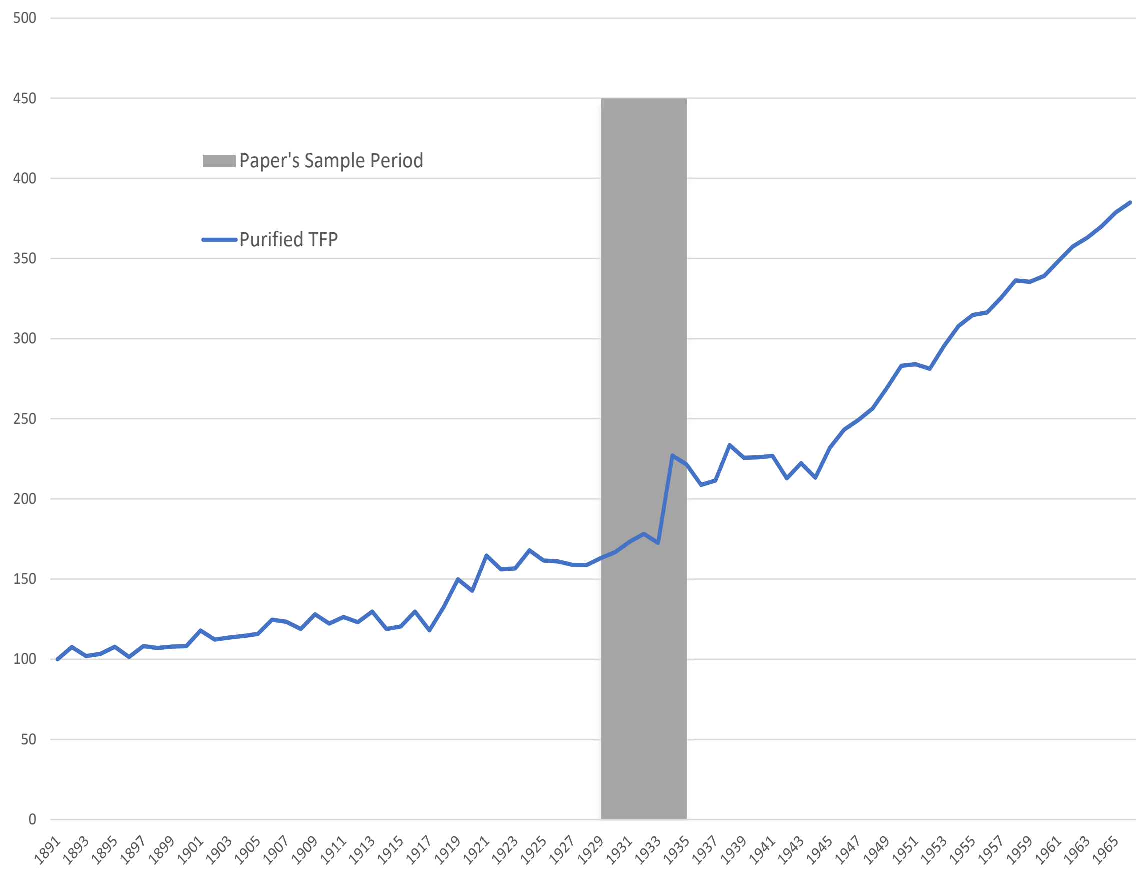
Table 1: **Descriptive Statistics.**

Industry	Establishment Count	Output Value (Millions of $)	Employment (Thousands)	Revenue Labor Productivity ($)
Cement	162	259.79	32.26	8,052.46
Concrete Products	1,756	82.23	14.39	5,714.41
Glass	239	299.12	64.81	4,615.6
Beverages	4,150	252.32	25.95	9,722.06
Steel Works	335	2,211.74	123.28	17,940.51
Ice Cream	2,506	313.76	21.3	14,732.24
Ice Manufactured	2,762	170.72	24.15	7,068.54
Macaroni	213	43.03	3.72	11,569.49
Malt	18	11.02	0.25	43,542.13
Agricultural Implements	229	274.66	41.02	6,696.33
Sugar Refining	21	507.39	13.91	36,472.21
Aircraft and Parts	123	71.67	14.63	4,898.94
Cotton goods	1,181	1,502.05	410.07	3,662.95
Linoleum	7	55.38	5.54	9,989.7
Planing Mills	3,258	446.65	71.16	6,277.06
Bone Black	26	10.12	0.98	10,300.05
Soap	174	182.47	9.63	18,944.31
Petroleum Refining	299	2,519.57	73.84	34,124.3
Rubber Tires	21	14.06	1.82	7,712.24
Radio Equipment	287	787.47	129.46	6,082.79
Total	17,767	10,015.22	1,082.17	9,254.75

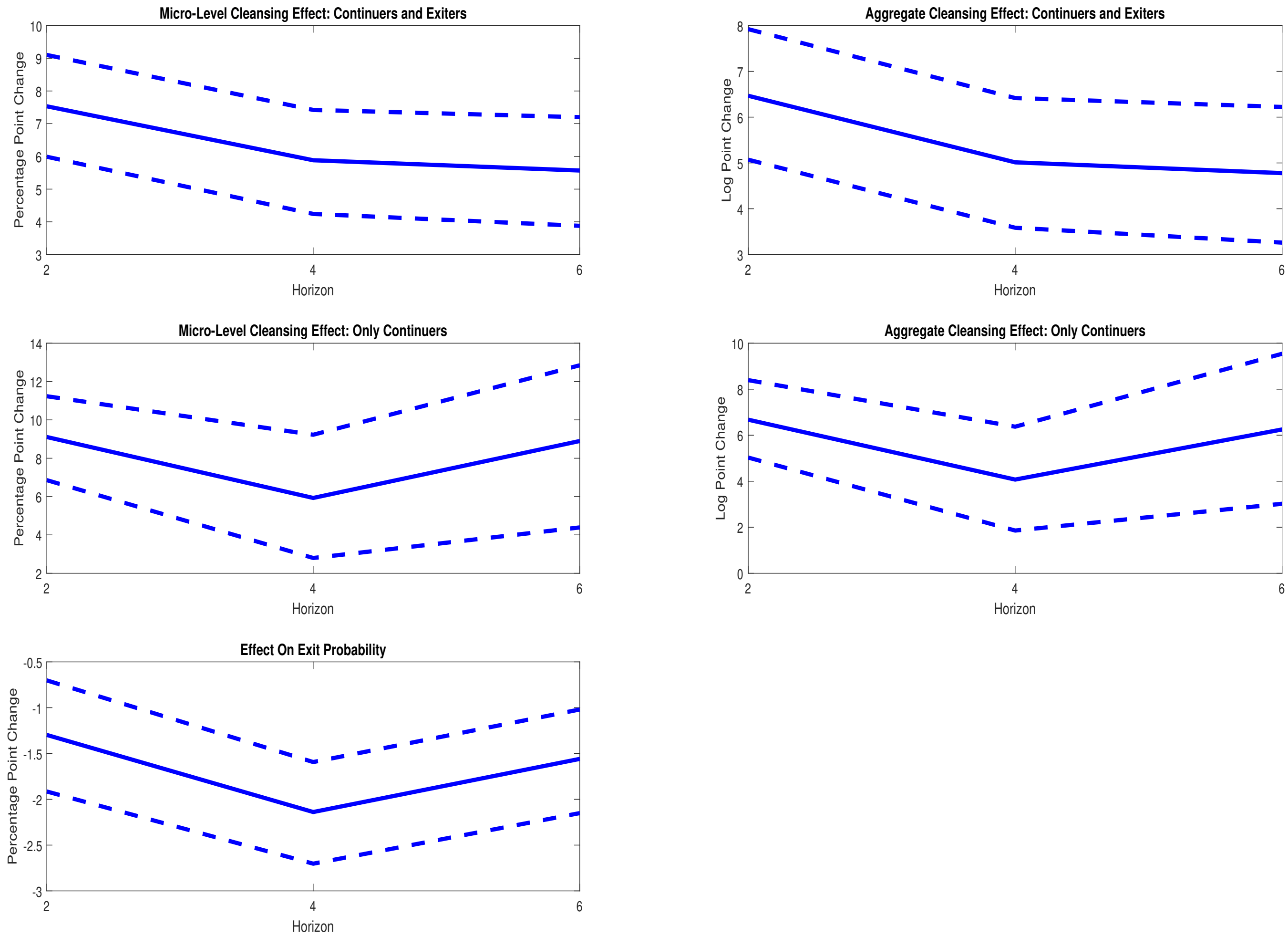
Notes: This table provides descriptive statistics for this paper's baseline sample of 20 industries and 17,767 establishments they contain. All variable values are for 1929. Output value corresponds to the value of produced output; employment refers to number of blue-collar workers (year average from monthly values); and revenue labor productivity is the ratio of output value to employment (the 'total' value for this variable divides the sample's total output value by total employment).

Figure 1: **Purified TFP.**



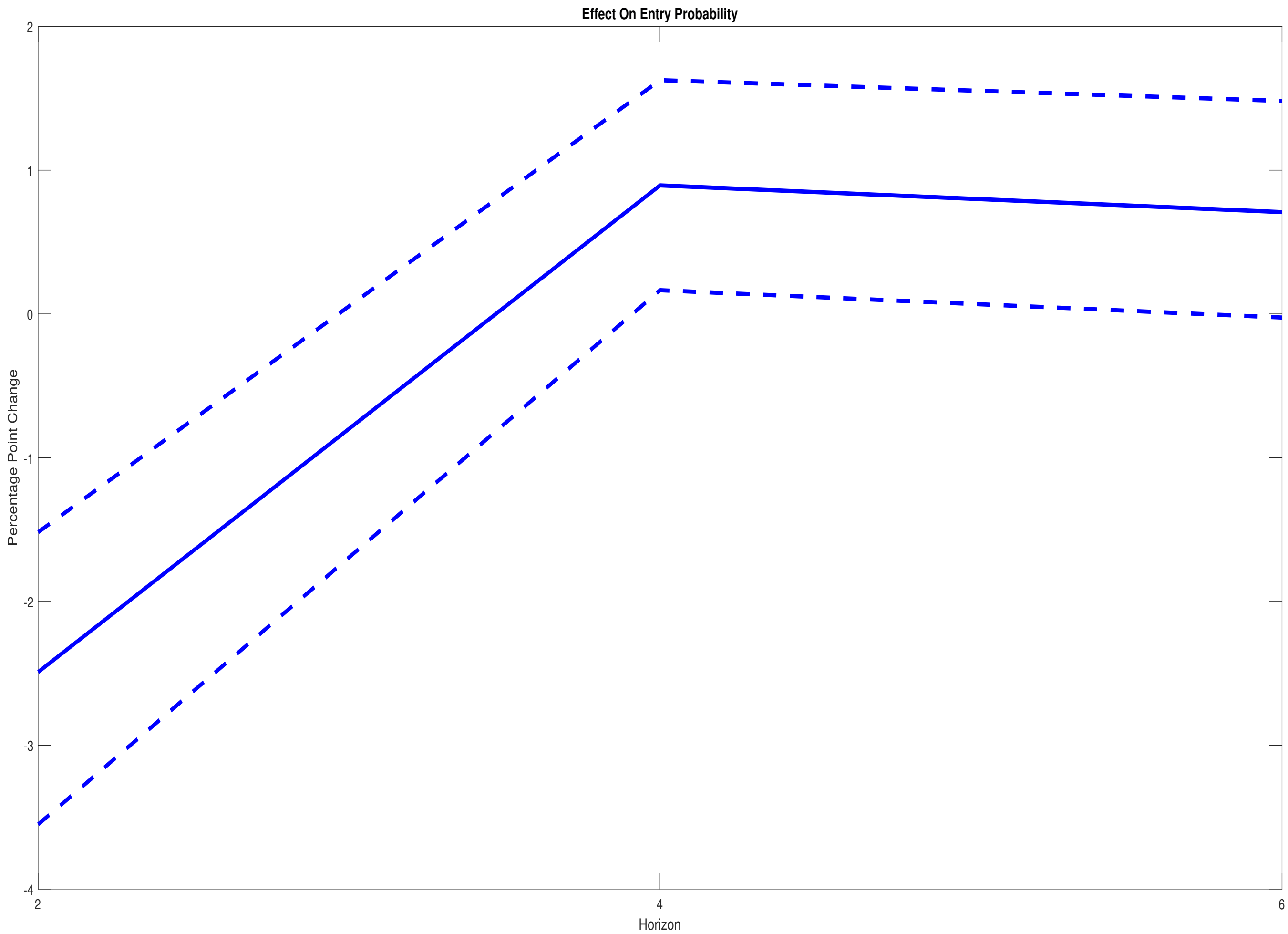
Notes: This figure shows the purified TFP series from Watanabe (2016) which accounts for increasing returns to scale, unobserved input utilization, and intermediate inputs. The series runs through 1891-1966 with the shaded area indicating this paper's sample period of 1929-1935. The series is in logged terms and normalized to 100 at the start of its sample period.

Figure 2: **Baseline Model: Cleansing-Induced Effect.**



Notes: The first column of this figure presents the estimated median (solid line) and 95% posterior band (dashed lines) values for the effect of being above the mean industry logged TFP by one standard deviation for this paper's three considered outcome variables: employment growth for continuing and exiting establishments, employment growth for only continuing establishments (i.e., growth conditional on survival), and exit dummy variable that receives one if the corresponding establishment exited in the relevant subsequent period and zero if otherwise. These outcome variables are measured from period 1929 to $1929 + h$ (for $h = 2, 4, 6$), i.e., the first column effectively shows the estimated median and 95% posterior band values for δ_h from Equation (13). The second column shows the estimated median and 95% posterior band values for $\hat{\mathbb{C}}_h$ from Equation (14) for both employment growth for continuing and exiting establishments and employment growth for only continuing establishments. Horizon (2 years, 4 years, 6 years) is on the x-axis. Micro-level cleansing effects and effect on exit probability are in terms of percentage point change; aggregate cleansing effects are in terms of log point change.

Figure 3: **Comparison of Entrants' and Exiters' Revenue Labor Productivity Levels.**



Notes: This figure presents the estimated median and 95% posterior band values for χ_h from Equation (15), which represents the effect of being above the mean industry logged revenue labor productivity by one standard deviation on the probability of being an entrant from 1929 to $1929 + h$ with the complementary event being an exiter from 1929 to $1929 + h$ ($h = 2, 4, 6$). Entrants' revenue labor productivity levels, which are observed in period $1929 + h$, are brought to common grounds with exiters' revenue labor productivity levels, which are observed in 1929, by multiplying the former by the ratio of the CPI in 1929 to the CPI in period $1929 + h$. Horizon (2 years, 4 years, 6 years) is on the x-axis. Effects are in terms of percentage point change.

Appendix A Suitability of Estimation Approach

The general environment described in Section 3.1 sufficed at describing the production and demand structure underlying the conceptual framework of this paper. While this was sufficient for fulfilling that section's purpose of forming a general conceptual base and guide for this paper's empirical analysis, the setting from Section 3.1 can be easily extended to a dynamic labor demand model with labor adjustment costs that in turn generates a general representation for employment growth which can facilitate a formal examination of the suitability of this paper's estimation approach for the identification of the micro-level and aggregate cleansing effects. This Appendix begins with a general depiction of such extension and proceeds by taking its implications as an input for the subsequent analysis of the suitability of this paper's estimation approach.

A.1 Theoretical Motivation for Empirical Specification and ψ Measurement

Recall the expression for nominal output implied by the production and demand structure of Section 3.1 (i.e., Equation (6)):

$$Y_{i,t} = e^{d_{i,c(i),t}} A_{i,t}^{\psi} L_{i,t}^{\alpha_L+\psi-1} K_{i,t}^{\alpha_K+\psi-1}. \tag{A.1}$$

As I show in the next section, regressing nominal output on the variables appearing in Equation (A.1) (i.e., $d_{i,c(i),t}$ (demand shock), $L_{i,t}$ (employment), and $K_{i,t}$ (capital)), and then regressing future employment growth on the residual from the latter regression results in an inconsistent estimate for the true micro-level cleansing effect whose inconsistency is a function of ψ.

Nevertheless, a standard and rather generic dynamic labor demand model, which also serves as theoretical motivation for this paper's empirical micro-level specification, allows me to obtain a downward biased measure of ψ. This in turn facilitates the embedding of a bias correction procedure into my estimation in a way that produces a downward biased estimate of the true micro-level cleansing effect. As such, this bias correction allows me to obtain a conservative estimate of the true micro-level cleansing effect which can be viewed as a lower bound of this effect. Notably, this bias correction is not relevant to the estimation of the aggregate cleansing effect, which manages to produce a lower bound estimate for its true counterpart using the non-bias-corrected micro-level cleansing effect estimate as the basis for the aggregate one.

I now turn to present this general dynamic labor demand model which in turn builds on the production and demand structure environment from Section 3.1. (This section's notation follows that from Section 3.1.)

A.1.1 Dynamic Cost Minimization

Optimization Problem. Denote the minimal value of discounted total costs of establishment i in period t by $V_{i,TC}(A_{i,t}, L_{i,t-1}, K_{i,t})$. Considering the production structure environment from Section 3.1, and assuming establishment i takes input prices as given,[24] this minimal value is obtained from the solution to the following Lagrangian-form Bellman equation:

$$V_{i,TC}(A_{i,t}, L_{i,t-1}, K_{i,t-1}) = \min_{M_{i,t}, L_{i,t}, K_{i,t}} [P_{i,t,M} M_{i,t} + W_{i,t} L_{i,t} + C_1(L_{i,t}, L_{i,t-1}) + \tag{A.2}$$
$$C_2(K_{i,t}, K_{i,t-1}) + R_{i,t} K_{i,t} + \mu_{i,t}(Z_{i,t} - A_{i,t} L_{i,t}^{\alpha_L} K_{i,t}^{\alpha_K}) + \kappa_{i,t}(Z_{i,t} - \varphi M_{i,t}) + \beta \mathbb{E}_t V_{i,TC}(A_{i,t+1}, L_{i,t}, K_{i,t})],$$

where (in terms of terminology first seen here) $P_{i,t,M}$ is the price of intermediate input; $W_{i,t}$ is nominal wage per employee paid by establishment i in period t; $C_1(L_{i,t}, L_{i,t-1})$ and $C_2(K_{i,t}, K_{i,t-1})$ are labor and capital adjustment cost functions which are general enough to have both convex and non-convex costs of adjustment; $R_{i,t}$ is the rental cost of capital facing establishment i (the associated period t capital $K_{i,t}$, like $L_{i,t}$, is assumed to be a year-average value (also see Footnote 29)); $\mu_{i,t}$ and $\kappa_{i,t}$ are Lagrange multipliers associated with the gross output production function constraint and gross-output-intermediate-input relation (where intermediate input is fully flexible), respectively; β is the discount factor; and $\mathbb{E}_t$ is the period t conditional expectations operator.

Marginal Cost. Denoting marginal cost by $MC_{i,t}$, the envelope condition for the value function from Equation (A.2) with respect to gross output in tandem with the first order condition of the

[24] Being exogenous to establishment i's cost minimization problem, these input prices should appear as additional arguments in the minimal cost value function. Nevertheless, for ease of exposition, I refrain from including them as such.

latter equation with respect to $M_{i,t}$ imply that[25]

$$MC_{i,t} \equiv \frac{\partial V_{i,TC}(A_{i,t}, L_{i,t-1}, K_{i,t-1}}{\partial Z_{i,t}} = \mu_{i,t} + \kappa_{i,t} = \mu_{i,t} + \frac{P_{i,t,M}}{\vartheta}. \tag{A.3}$$

Note that I substitute out $\kappa_{i,t}$ with $\frac{P_{i,t,M}}{\vartheta}$ as this substitution will facilitate my measurement of ψ (where $\psi - 1$ is the inverse demand elasticity), which is the central issue of this section and to which I turn in the next section. Also noteworthy is that a non-convex nature of $C_1(L_{i,t}, L_{i,t-1})$ and/or $C_2(K_{i,t}, K_{i,t-1})$ would imply that $\mu_{i,t} > 0$ when establishment i adjusts its (quasi-fixed) labor and/or capital inputs while implying that $\mu_{i,t} = 0$ when establishment i does not adjust either of the labor and capital inputs.

A.1.2 Profit Maximization

Optimization Problem. Denote the maximal value of discounted revenues of establishment i in period t by $V_{i,R}(A_{i,t}, d_{i,c(i),t})$, where $d_{i,c(i),t}$ is the output demand shock from Equation (4). Considering the demand structure environment from Section 3.1 (specifically, Equation (4)), this maximal value is obtained from the solution to the following Bellman equation:

$$V_{i,R}(A_{i,t}, d_{i,c(i),t}) = \max_{Z_{i,t}} [e^{d_{i,c(i),t}} Z_{i,t}^{\psi} + \beta \mathbb{E}_t V_{i,R}(A_{i,t+1}, d_{i,c(i),t+1})]. \tag{A.4}$$

And the maximal value of discounted profits for establishment i, denoted by $V_{i,\Pi}(A_{i,t}, d_{i,c(i),t}, L_{i,t-1}, K_{i,t})$, is given by

$$V_{i,\Pi}(A_{i,t}, d_{i,c(i),t}, L_{i,t-1}, K_{i,t-1}) = V_{i,R}(A_{i,t}, d_{i,c(i),t}) - V_{i,TC}(A_{i,t}, L_{i,t-1}, K_{i,t-1}). \tag{A.5}$$

First Order Condition. The first order condition of Equation (A.5) with respect to $Z_{i,t}$ gives

$$\psi = \frac{MC_{i,t}}{P_{i,t,Z}} = \frac{\mu_{i,t}}{P_{i,t,Z}} + \frac{P_{i,t,M}}{\vartheta P_{i,t,Z}} = \frac{\mu_{i,t}}{P_{i,t,Z}} + \frac{P_{i,t,M} M_{i,t}}{P_{i,t,Z} Z_{i,t}}, \tag{A.6}$$

where in moving from the second to third equality I substituted Equation (A.3) into Equation (A.6); and in moving from the third to last equality I have substituted in the gross-output-intermediate-input relation $Z_{i,t} = \vartheta M_{i,t}$.

[25] A remark is in order about the validity of these envelope and first order conditions given the non-convex setting allowed for by the general labor and capital adjustment cost functions $C_1(L_{i,t}, L_{i,t-1})$ and $C_2(K_{i,t}, K_{i,t-1})$ which presumably undermines this validity. A recent paper by Clausen and Strub (2020) shows that such conditions are also valid even in the presence of a non-convex setting which suffers from kinks (as the general model here).

Restriction on ψ. Notably, since marginal cost is positive and does not exceed output price, Equation (A.6) implies that $0 < \psi \leq 1$, i.e., that the elasticity of output demand $\frac{1}{\psi - 1}$ is larger than one in absolute value. This restriction on the value of ψ, being imposed upon by establishments' optimal behavior, is consistent with the empirical evidence from Foster et al. (2008) for modern establishment-level data which finds industry-specific demand elasticities that are larger than one in absolute value for nine of their ten considered industries.

A.1.3 Measurement of ψ

As I show in the next section, if $\psi = 1$ then my estimation procedure is consistent for the true micro-level cleansing effect. In particular, the estimated micro-level cleansing effect is equal to the ratio of the true cleansing effect and ψ. It is therefore possible, in principle, to eliminate the upward bias from ψ by multiplying the dependent variable from Regression (12) (nominal output) by ψ^{-1}.

However, since I can only observe $\frac{P_{i,t,M} M_{i,t}}{P_{i,t,Z} Z_{i,t}}$ in the data and not the additional source of marginal cost given by μ which comes from the adjustment of the less flexible labor input factor, I take a conservative approach toward the measurement of ψ. In particular, I assign a lower bound value for ψ given by the industry-specific cross-sectional average of $\frac{P_{i,t,M} M_{i,t}}{P_{i,t,Z} Z_{i,t}}$ in the data and, for each industry, I multiply the nominal output variable from Regression (12) by the inverse of this cross-sectional average.[26] This value is a lower bound for ψ because the additional source of marginal cost given by μ is necessarily positive and hence the multiplication of my empirical nominal output variable by the inverse of this value overly corrects for the bias from ψ.

For completeness and comparison purposes, prior to showing the asymptotic behavior of my bias-corrected estimation of the micro-level cleansing effect, I first show the asymptotic behavior of the non-bias-corrected one. This is what I turn to next. (The non-bias-corrected estimation procedure is also what underlies the estimation of the aggregate cleansing effect, where the latter's ability to produce a lower bound estimate for the true aggregate cleansing effect does not hinge

[26] As in Section 3, this section also continues to assume for the sake of exposition that there is a single industry. Allowing for more than one industry would not change the asymptotic results obtained in this section given that the OLS estimate of the cleansing effect would then merely be a weighted average of the industry-specific OLS estimates. However, since this would complicate exposition without sacrificing the validity of the this section's results, I prefer to continue with the single-industry expositional setting.

on the bias correction that is needed for the estimation of the micro-level cleansing effect. In fact, this bias correction produces a larger estimated aggregate cleansing effect than that obtained from using the non-bias-corrected estimation procedure.)

A.2 Identification of True Micro-Level Cleansing Effect: Non-Bias-Corrected Estimation

A.2.1 True Specification for $g_{i,t,t+h}$

As discussed in Decker et al. (2020), a generic dynamic labor demand model of the kind presented in the previous section produces a rather generic representation for the growth rate of establishment i's employment from period t to $t+h$ (denoted as in Section 4.2 by $g_{i,t,t+h}$, with $h = 2,4,6$ representing the future horizon) given by[27,28]

$$g_{i,t,t+h} = \beta_{1,h} a_{i,t} + \beta_{2,h} l_{i,t} + \beta_{3,h} k_{i,t} + \beta_{4,h} d_{i,c(i),t} + \epsilon_{i,t+h}, \tag{A.7}$$

where $a_{i,t}$, $l_{i,t}$, and $k_{i,t}$[29] are logs of establishment i's (physical) TFP, employment, and physical capital, respectively, with corresponding coefficients β_1, β_2, and β_3; $d_{i,c(i),t}$ is the demand shock from Equation (4) with corresponding coefficient $\beta_{4,h}$, where $c = 1,2,...,C$ $(C < I)$ represents a location comprising establishments whose demand shock is common owing to it being rooted in

[27] Granted, theoretical models of dynamic labor demand imply an employment growth policy function that embodies a link between period t state variables and employment growth from period t to period $t+1$, not $t+h$ for $h > 1$ as in Equation (A.7). Nevertheless, this does not undermine the validity of Equation (A.7), or the estimated empirical Specification (13) for that matter, because these equations can be viewed as the outcome of recursively substituting out the $t+s, t+s+1$ period pairs (with $s = 0,1,...,5$) such that employment growth from period t to period $t+h$ is a function of period t state variables.

[28] It is noteworthy that the reduced form true specification from Equation (A.7) corresponds in general to the theory-consistent one from Decker et al. (2020) only that I also include in mine initial physical capital. This extension is due to the fact that my conceptual framework also includes physical capital as factor input while theirs abstracted from this inclusion.

[29] Note that, while it is standard in theoretical settings to treat $K_{i,t}$ as a predetermined state variable in period t (representing capital at the end of period $t-1$), such treatment is more natural in settings with higher frequency data dimensions (e.g., quarterly). The reason for this is that in these settings the resultant time dimension is sufficiently short for the initial capital stock to be solely considered as the capital relevant for production. For the annual frequency underlying this paper's theoretical and empirical analysis it is more reasonable to treat $K_{i,t}$ as a year-average value of physical capital so as to properly account for its role in facilitating production throughout the year-long associated production period. While my period t empirical measure of physical capital is measured for the end of period t, as requested by the COM from surveyed establishments, this empirical measure can still be viewed as a reasonable proxy for its year-average theoretical counterpart as it embodies the full year-long capital accumulation employed for production throughout the period.

horizontal differentiation (also see the discussion from Page 9); and $\epsilon_{i,t+1}$ is an error term capturing period $t+h$ idiosyncratic shocks to input prices that are uncorrelated with $a_{i,t}$, $l_{i,t}$, $k_{i,t}$, and $d_{i,c(i),t}$. The presence of $a_{i,t}$ and $d_{i,c(i),t}$ in Equation (A.7), rather than $a_{i,t+h}$ and $d_{i,c(i),t+h}$, can be justified on the basis of some assumed auto-regressive process underlying $a_{i,t}$ and $d_{i,c(i),t}$.

β_1 is the true cleansing effect object this paper seeks to identify. For convenience, I assume that $g_{i,t,t+h}$, $a_{i,t}$, $l_{i,t}$, $k_{i,t}$, and $d_{i,c(i),t}$ are all cast in terms of deviation from their corresponding industry means. (Moreover, as in section 3, for ease of exposition and without loss of generality, I continue to assume that there is a single industry comprising the I establishments.)

A.2.2 Estimated Specification for $g_{i,t,t+h}$

Because my data does not allow me to observe a_t (also see the related discussion from Page 16), I estimate the following two-equation system as a substitute specification with respect to Equation (A.7):[30]

$$y_{i,t} = \rho_1 \mathbb{D}_{i,1,t} + \rho_2 \mathbb{D}_{i,2,t} + \cdots + \rho_C \mathbb{D}_{i,C,t} + \gamma_{1,h} l_{i,t} + \gamma_{2,h} k_{i,t} + u_{i,t}, \tag{A.8}$$

$$g_{i,t,t+h} = \delta_h \hat{u}_{i,t} + v_{i,t+h}, \tag{A.9}$$

where the first equation is meant to extract an estimate of $a_{i,t}$, which is denoted by $\hat{u}_{i,t}$, i.e., the estimated residual from this equation; and the second equation simply regresses employment growth on this estimated residual. County fixed effects ρ_c are now included to account for the unobserved demand shock, where counties are indexed by $c = 1, 2, ..., C$ ($C < I$) and $\mathbb{D}_{i,c,t}$ is a dummy variable equaling one if establishment i operates in county c.[31] The important question

[30] As explained at the end of Section 4.2, while System (A.8)-(A.9) is asymptotically equivalent to a single equation that regresses $g_{i,t,t+h}$ on all of the explanatory variables of Equation (A.8) as well as $y_{i,t}$, the merit of this system lies in its facilitation of appropriate inference for the bottom-up econometric approach which estimates the aggregate cleansing effect. In particular, this two-equation system is able to explicitly account for uncertainty in the estimation of the $a_{i,t}$ series which serves as an important input for the estimation of the aggregate cleansing effect.

[31] To facilitate the asymptotic analysis of the suitability of my estimation procedure, I present the county fixed effects explicitly in Equation (A.8) as opposed to implicitly as in the empirical specification from Equation (12). It is also noteworthy that Equation (A.8) is different from the empirical specification from Equation (12) only in that the industry fixed effects are now absent for ease of exposition; and, also for ease of exposition, Equation (A.9) is different from the empirical specification from Equation (13) only in that the multi-establishment fixed effects are now absent. Lastly, also note that estimated System (A.8)-(A.9) keeps subscript t in line with true Specification (A.7) as opposed to System (12)-(13) which omits it given that for the entire empirical analysis $t = 1929$.

that emerges from System (A.8)-(A.9) is what the asymptotic behavior of the estimate of δ_h is with respect to its counterpart $\beta_{1,h}$.

A.2.3 What the Estimated δ_h Captures

Taking logs of Equation (A.1) (Equation (6) in the text) gives $y_{i,t} = d_{i,c(i),t} + \psi a_{i,t} + (\alpha_L + \psi - 1) l_{i,t} + (\alpha_K + \psi - 1) k_{i,t}$. This structural representation of logged nominal output $y_{i,t}$ will assist us below in the asymptotic examination of δ_h's estimate.

First Stage of Estimation Procedure. The first stage of my estimation procedure consists of estimation of Equation (A.8). Let $\mathbb{D}_{\mathbf{I},\mathbf{C},t} = [\mathbb{D}_{1,1,t}, ..., \mathbb{D}_{I,1,t}; \mathbb{D}_{1,2,t}, ..., \mathbb{D}_{I,2,t}; ...; \mathbb{D}_{1,C,t}, ..., \mathbb{D}_{I,C,t}]'$ be the stacked county fixed effect dummy matrix; and let $X_{\mathbf{I},t} = [l_{1,t}, ..., l_{I,t}; k_{1,t}, ..., k_{I,t}; \mathbb{D}_{1,\mathbf{C},t}, ..., \mathbb{D}_{I,\mathbf{C},t}]'$ and $y_{\mathbf{I},t} = [y_{1,t} ... y_{I,t}]'$ be the stacked data matrices that underlie Regression (A.8). With this notation in place, the expression for the estimated residual from the latter regression, denoted by $\hat{u}_{\mathbf{I},t} = [\hat{u}_{1,t} ... \hat{u}_{I,t}]'$, can be written as

$$\hat{u}_{\mathbf{I},t} = lp_{\mathbf{I},t} - X_{\mathbf{I},t}(X'_{\mathbf{I},t}X_{\mathbf{I},t})^{-1}X'_{\mathbf{I},t}lp_{\mathbf{I},t} = d_{\mathbf{I},t} + \psi a_{I,t} + (\alpha_L + \psi - 1)l_{I,t} + \tag{A.10}$$
$$(\alpha_K + \psi - 1)k_{\mathbf{I},t} - X_{\mathbf{I},t}(X'_{\mathbf{I},t}X_{\mathbf{I},t})^{-1}X'_{\mathbf{I},t}(d_{\mathbf{I},t} + \psi a_{\mathbf{I},t} + (\alpha_L + \psi - 1)l_{\mathbf{I},t} + (\alpha_K + \psi - 1)k_{\mathbf{I},t}) =$$
$$\psi a_{\mathbf{I},t} - \psi X_{\mathbf{I},t}(X'_{\mathbf{I},t}X_{\mathbf{I},t})^{-1}X'_{\mathbf{I},t}a_{\mathbf{I},t}.$$

where $a_{\mathbf{I},t} = [a_{1,t}, ..., a_{I,t}]'$, $l_{\mathbf{I},t} = [l_{1,t}, ..., l_{I,t}]'$, $k_{\mathbf{I},t} = [k_{1,t}, ..., k_{I,t}]'$, and $d_{\mathbf{I},t} = [d_{1,c(1),t}, ..., d_{I,c(I),t}]'$; and in going from the first to third equality in Equation (A.10) I have substituted the relation $y_{\mathbf{I},t} = d_{\mathbf{I},t} + \psi a_{\mathbf{I},t} + (\alpha_L + \psi - 1)l_{\mathbf{I},t} + (\alpha_K + \psi - 1)k_{\mathbf{I},t}$ into that equation, while making use of the fact that, since $X_{\mathbf{I},t}$ consists of the data vectors $l_{\mathbf{I},t}$, $k_{\mathbf{I},t}$, and $\mathbb{D}_{\mathbf{I},t}$, terms relating to the latter data vectors can be perfectly predicted by $X_{\mathbf{I},t}$ and thus get canceled out.

Importantly, this cancellation also applies to the prediction error for $d_{\mathbf{I},t}$, i.e., $d_{\mathbf{I},t} - X_{\mathbf{I},t}(X'_{\mathbf{I},t}X_{\mathbf{I},t})^{-1}X'_{\mathbf{I},t}d_{\mathbf{I},t} = 0$. To see why the latter equality is true, recall that $d_{\varrho,c(\varrho),t} = d_{\varsigma,c(\varsigma),t}$ for all $\varrho, \varsigma \in c$ (i.e., $c(\varrho) = c(\varsigma)$). Hence, simply assigning $\rho_c = d_{i,c(i),t}$ for all i's corresponding to c produces $d_{i,c(i),t} = \rho_1 \mathbb{D}_{i,1,t} + \rho_2 \mathbb{D}_{i,2,t} + \cdots + \rho_C \mathbb{D}_{i,C,t}$, i.e., $d_{I,t}$ is a linear combination of the vectors comprising $D_{I,t}$. The identifying assumption underlying this result is that the average county c is sufficiently small so that $\mathbb{D}_{\mathbf{I},\mathbf{C},t}$'s column dimension is sufficiently large for completely capturing horizontal-differentiation-induced demand differences. To the extent that this is not the case, there will be a bias from the presence of the demand shock. However, the county fixed effects I use are arguably fine enough to capture well such demand differences, encompassing a total of 1,992 counties with the average industry containing on average 0.44 establishments in each county.

Equation (A.10) formally shows that the residual from regressing nominal output on employment, capital, and the county fixed effect dummy matrix would only identify TFP if $\psi = 1$ and $\operatorname*{plim}_{I\to\infty} X_{\mathbf{I},t}(X'_{\mathbf{I},t}X_{\mathbf{I},t})^{-1}X'_{\mathbf{I},t}a_{\mathbf{I},t} \neq 0$. The first condition implies perfectly elastic demand for establishment-level output, which is at odds with evidence from modern establishment-level data (Foster et al. (2008)). And the invalidity of the second condition precisely speaks to the endogeneity issue facing production function OLS estimation: since standard models generically indicate that there should clearly be a cross-sectional dependence of employment and capital on TFP, i.e., $\operatorname*{plim}_{I\to\infty} X_{\mathbf{I},t}(X'_{\mathbf{I},t}X_{\mathbf{I},t})^{-1}X'_{\mathbf{I},t}a_{\mathbf{I},t} \neq 0$, such estimation fails at recovering TFP.

Although the cross-sectional TFP series itself is clearly not identified in this setting, understanding what its estimated effect on future employment growth captures is still very much worthwhile. Toward this end, I now turn to the second stage of my estimation procedure.

Second Stage of Estimation Procedure. The second stage of my estimation procedure consists of estimation of Equation (A.9), i.e., regressing $g_{\mathbf{I},t,t+h} = [g_{1,t,t+h}, ..., g_{I,t,t+h}]'$ on $\hat{u}_{\mathbf{I},t}$. It is useful to denote forecasted logged TFP (in deviation from industry mean) $X_{\mathbf{I},t}(X'_{\mathbf{I},t}X_{\mathbf{I},t})^{-1}X'_{\mathbf{I},t}a_{\mathbf{I},t}$ by $\hat{a}_{\mathbf{I},t}$ and to note that $a_{\mathbf{I},t} = \psi^{-1}\hat{u}_{\mathbf{I},t} + \hat{a}_{\mathbf{I},t}$. This in turn yields the following expression and associated asymptotic result for the estimate of δ_h ($\hat{\delta}_h$):

$$\operatorname*{plim}_{I\to\infty}\hat{\delta}_h = \operatorname*{plim}_{I\to\infty}(\hat{u}'_{\mathbf{I},t}\hat{u}_{\mathbf{I},t})^{-1}\hat{u}'_{\mathbf{I},t}g_{\mathbf{I},t,t+h} = \operatorname*{plim}_{I\to\infty}(\hat{u}'_{\mathbf{I},t}\hat{u}_{\mathbf{I},t})^{-1}\hat{u}'_{\mathbf{I},t}(\beta_{1,h}a_{\mathbf{I},t} + \beta_{2,h}l_{\mathbf{I},t} + \beta_{3,h}k_{\mathbf{I},t} + \beta_{4,h}d_{\mathbf{I},t} + \epsilon_{\mathbf{I},t+h}) = \operatorname*{plim}_{I\to\infty}(\hat{u}'_{\mathbf{I},t}\hat{u}_{\mathbf{I},t})^{-1}\hat{u}'_{\mathbf{I},t}\left(\frac{\beta_{1,h}}{\psi}\hat{u}_{\mathbf{I},t} + \beta_{1,h}\hat{a}_{\mathbf{I},t}\right) = \frac{\beta_{1,h}}{\psi} > \beta_{1,h}. \tag{A.11}$$

Note that in going from the first to last equality from Equation (A.11) I have made use of the fact that, being the estimated residual from Equation (A.8), $\hat{u}_{\mathbf{I},t}$ is uncorrelated with all variables belonging to $X_{\mathbf{I},t}$ as well as $\hat{a}_{\mathbf{I},t}$ as the latter forecast is conditioned on $X_{\mathbf{I},t}$. Moreover, I have also made use of the assumption that $\epsilon_{\mathbf{I},t+1}$ ($\epsilon_{\mathbf{I},t+1} = [\epsilon_{1,t+1}...\epsilon_{I,t+1}]'$) is an error term that is uncorrelated with establishment-level employment, capital, county fixed effect dummy matrix, and TFP.

The main takeaway from Equation (A.11) is that $\hat{\delta}_h$ is only consistent for $\beta_{1,h}$ if $\psi = 1$. This inconsistency clearly reflects upward biasedness, which would be discouraging if I were to use my raw estimation procedure to obtain the micro-level cleansing effect estimate. However, as explained in the beginning of Section A.1, this inconsistency result actually opens the door for applying a bias-correction procedure to the raw estimation procedure which yields a lower bound estimate for $\beta_{1,h}$. This conservative bias correction based estimation approach is what I turn to discuss next.

A.3 Identification of True Micro-Level Cleansing Effect: Bias-Corrected Estimation

On the basis of Equation (A.6), this section puts forward a bias-corrected estimation approach that assigns a lower bound value for ψ (denoted by $\tilde{\psi} < \psi$) given by the industry-specific cross-sectional average of $\frac{P_{i,t,M} M_{i,t}}{P_{i,t,Z} Z_{i,t}}$ in the data where for each industry I multiply $y_{i,t}$ from Equation (A.8) by the inverse of this cross-sectional average. In particular, I construct a bias-corrected nominal output variable $\tilde{y}_{i,t} = \tilde{\psi}^{-1} y_{i,t}$ and enter it into estimated Regression (A.8) in place of $y_{i,t}$.[32]

A.3.1 True Specification for $g_{i,t,t+h}$

The true specification is the same as that from Section A.2.1 (i.e., Equation (A.7)).

A.3.2 Estimated Specification for $g_{i,t,t+h}$

As explained in the beginning of this section, the estimated specification for the bias-corrected procedure replaces $y_{i,t}$ with $\tilde{y}_{i,t} = \tilde{\psi}^{-1} y_{i,t}$, resulting in the following modified estimated two-

[32]Recall that for expositional purposes I assume there is only one industry comprising the I establishments while in the actual empirical analysis I apply this data correction for each of the 20 industries. However, as also explained in Footnote 26, having more than one industry has no bearing on the asymptotic results of this section as the resulting micro-level cleansing effect OLS estimate would simply be a weighted average of the industry-specific estimates. Hence, the single-industry assumption is made merely to ease exposition and without loss of generality.

equation specification:

$$\tilde{y}_{i,t} = \rho_{bc,1}\mathbb{D}_{i,1,t} + \rho_{bc,2}\mathbb{D}_{i,2,t} + \cdots + \rho_{bc,C}\mathbb{D}_{i,C,t} + \gamma_{1,bc,h}l_{i,t} + \gamma_{2,bc,h}k_{i,t} + u^{bc}_{i,t}, \tag{A.12}$$

$$g_{i,t,t+h} = \delta_{bc,h}\hat{u}^{bc}_{i,t} + v^{bc}_{i,t+h}, \tag{A.13}$$

where I have added subscript and superscript bc to the coefficients and residuals in these regressions, respectively, to clarify that these regressions underly the bias-corrected estimation procedure.

A.3.3 What the Bias-Corrected Estimated $\delta_{bc,h}$ Captures

First Stage of Estimation Procedure. The only difference in this part's analysis relative to the corresponding one from Section A.2.3 is that $\tilde{y}_{i,t}$ replaces $y_{i,t}$. Hence, keeping with the same terminology from that section's analysis, the expression for the estimated residual from Equation (A.12), denoted by $\hat{u}^{bc}_{\mathbf{I},t} = [\hat{u}^{bc}_{1,t}...\hat{u}^{bc}_{I,t}]'$, can be written as

$$\hat{u}^{bc}_{\mathbf{I},t} = \tilde{y}_{\mathbf{I},t} - X_{\mathbf{I},t}(X'_{\mathbf{I},t}X_{\mathbf{I},t})^{-1}X'_{\mathbf{I},t}lp_{\mathbf{I},t} = \tilde{\psi}^{-1}(d_{\mathbf{I},t} + \psi a_{I,t} + (\alpha_L + \psi - 1)l_{I,t} + \tag{A.14}$$
$$(\alpha_K + \psi - 1)k_{\mathbf{I},t}) - \tilde{\psi}^{-1}X_{\mathbf{I},t}(X'_{\mathbf{I},t}X_{\mathbf{I},t})^{-1}X'_{\mathbf{I},t}(d_{\mathbf{I},t} + \xi_{\mathbf{I},t} + \psi a_{\mathbf{I},t} + (\alpha_L + \psi - 1)l_{\mathbf{I},t} + (\alpha_K + \psi - 1)k_{\mathbf{I},t}) =$$
$$\tilde{\psi}^{-1}\psi a_{\mathbf{I},t} - \tilde{\psi}^{-1}\psi X_{\mathbf{I},t}(X'_{\mathbf{I},t}X_{\mathbf{I},t})^{-1}X'_{\mathbf{I},t}a_{\mathbf{I},t}.$$

Second Stage of Estimation Procedure. It is useful to recall the previous section's denotation of forecasted logged TFP $X_{\mathbf{I},t}(X'_{\mathbf{I},t}X_{\mathbf{I},t})^{-1}X'_{\mathbf{I},t}a_{\mathbf{I},t}$ by $\hat{a}_{\mathbf{I},t}$ and to note that $a^{bc}_{\mathbf{I},t} = \tilde{\psi}\psi^{-1}\hat{u}_{\mathbf{I},t} + \hat{a}_{\mathbf{I},t}$. This in turn yields the following expression and associated asymptotic result for the estimate of $\delta_{bc,h}$ ($\hat{\delta}_{bc,h}$):

$$\underset{I\to\infty}{\text{plim}}\,\hat{\delta}_{bc,h} = \underset{I\to\infty}{\text{plim}}(\hat{u}^{bc\prime}_{\mathbf{I},t}\hat{u}^{bc}_{\mathbf{I},t})^{-1}\hat{u}^{bc\prime}_{\mathbf{I},t}g_{\mathbf{I},t,t+h} = \underset{I\to\infty}{\text{plim}}(\hat{u}^{bc\prime}_{\mathbf{I},t}\hat{u}^{bc}_{\mathbf{I},t})^{-1}\hat{u}^{bc\prime}_{\mathbf{I},t}(\beta_{1,h}a_{\mathbf{I},t} + \beta_{2,h}l_{\mathbf{I},t} + \tag{A.15}$$
$$\beta_{3,h}k_{\mathbf{I},t} + \beta_{4,h}d_{\mathbf{I},t} + \epsilon_{\mathbf{I},t+h}) = \underset{I\to\infty}{\text{plim}}(\hat{u}^{bc\prime}_{\mathbf{I},t}\hat{u}^{bc}_{\mathbf{I},t})^{-1}\hat{u}^{bc\prime}_{\mathbf{I},t}\left(\tilde{\psi}\frac{\beta_{1,h}}{\psi}\hat{u}_{\mathbf{I},t} + \beta_{1,h}\hat{a}_{\mathbf{I},t}\right) = \tilde{\psi}\frac{\beta_{1,h}}{\psi} < \beta_{1,h}.$$

Equation (A.15) formally shows that the bias-corrected OLS estimate of the micro-level cleansing effect converges in probability to a value that is lower than the true cleansing effect $\beta_{1,h}$ (owing to the fact that $\tilde{\psi} < \psi$). Note that if I were able to observe the ratio of the labor- and capital-input-induced marginal cost to output price (i.e., $\frac{\mu_{i,t}}{P_{i,t}}$) then I would be able to obtain a precise measure of ψ by adding to the original ψ measure ($\tilde{\psi}$) the cross-sectional average of $\frac{\mu_{i,t}}{P_{i,t}}$, in which case the bias-corrected estimate would be consistent for the true micro-level cleansing effect. But since the unobserved cross-sectional average of $\frac{\mu_{i,t}}{P_{i,t}}$ is positive, we know that $\frac{\tilde{\psi}}{\psi} < 1$ and hence the micro-level cleansing effect estimate from Equation (A.15) underestimates its true counterpart object.

In sum, my bias-corrected estimation approach provides a conservative, lower bound estimate for the true micro-level cleansing effect. As such, it is able to deliver results on the micro-level cleansing effect that are meaningfully informative about the true micro-level cleansing effect.

A.4 Identification of True Aggregate Cleansing Effect

While the raw estimate of the micro-level cleansing effect is upward biased with respect to its true counterpart, using this raw estimate along with the raw estimated TFP series results in an estimate of the aggregate cleansing effect that understates its true counterpart. Hence, for the estimated aggregate cleansing effect, my focus shifts to the raw estimated micro-level cleansing effect. (In fact, using the bias-corrected micro-level cleansing effect and TFP series estimates actually produces a higher estimated aggregate cleansing effect than that obtained from using the raw estimates.) This section shows this underestimation of the true aggregate cleansing effect.

A.4.1 True Aggregate Cleansing Effect

Definition of True Aggregate Cleansing Effect. Recall this paper's definition of the true aggregate cleansing effect, denoted by $\mathbb{C}$, as given by Equation (9) in the text:

$$\mathbb{C}_{t,t+h} = \sum_{i=1}^{I} \mathbb{E}_t\big(w_{i,t+h} \bigm| a_{i,t}\big)\, a_{i,t} - \sum_{i=1}^{I} w_{i,t} a_{i,t}, \tag{A.16}$$

where $t = 1929$ and $h = 2, 4, 6$; and $\mathbb{E}_t\big(w_{i,t+h} \bigm| a_{i,t}\big)$ represents establishment i's expected employment share at horizon $t+h$ conditional on initial logged TFP (in deviation from industry mean).

Expression for $\mathbb{E}_t\big(w_{i,t+h} \bigm| a_{i,t}\big)$. To obtain an explicit expression for $\mathbb{E}_t\big(w_{i,t+h} \bigm| a_{i,t}\big)$, we need to combine $\mathbb{E}_t\big(g_{i,t,t+h} \bigm| a_{i,t}\big) = \beta_{1,h} a_{i,t}$ with the relation between future employment share and growth $w_{i,t+h} = \frac{L_{i,t}(1+g_{i,t,t+h})}{\sum_{i=1}^{I} L_{i,t}(1+g_{i,t,t+h})}$. (Optimal prediction $\mathbb{E}_t\big(g_{i,t,t+h} \bigm| a_{i,t}\big) = \beta_{1,h} a_{i,t}$ is obtained from applying the latter conditional expectations operator to the true specification from Equation (A.7).) Since

$w_{i,t+h}$ is a nonlinear function of $g_{i,t,t+h}$, it is apriori unclear that

$$\mathbb{E}_t\big(w_{i,t+h} \mid a_{i,t}\big) = \frac{L_{i,t}\Big(1 + \mathbb{E}_t\big(g_{i,t,t+h} \mid a_{i,t}\big)\Big)}{\sum\limits_{i=1}^{I} L_{i,t}\Big(1 + \mathbb{E}_t\big(g_{i,t,t+h} \mid a_{i,t}\big)\Big)} = \frac{L_{i,t}(1 + \beta_{1,h} a_{i,t})}{\sum\limits_{i=1}^{I} L_{i,t}(1 + \beta_{1,h} a_{i,t})} \tag{A.17}$$

constitutes a sufficiently precise approximation of the true conditional expectation of the future employment share. However, in derivations that are not shown here but are available upon request, I have applied a second-order Taylor approximation of the first moment of $w_{i,t+h} = \frac{L_{i,t}(1+g_{i,t,t+h})}{\sum_{i=1}^{I} L_{i,t}(1+g_{i,t,t+h})}$ and found that

$$\mathbb{E}_t\big(w_{i,t+h} \mid a_{i,t}\big) = \frac{L_{i,t}\Big(1 + \mathbb{E}_t\big(g_{i,t,t+h} \mid a_{i,t}\big)\Big)}{\sum\limits_{i=1}^{I} L_{i,t}\Big(1 + \mathbb{E}_t\big(g_{i,t,t+h} \mid a_{i,t}\big)\Big)} + O(I^{-4}), \tag{A.18}$$

i.e., the approximation error from Equation (A.17) becomes very negligible as sample size becomes asymptotic with this error shrinking to zero at the same rate as $\lim\limits_{I \to \infty} I^{-4}$. While the analysis of the aggregate cleansing effect does not rely on asymptotics but rather takes as given my empirical sample (and its size), as opposed to the micro-level cleansing effect analysis, the baseline sample size of 17,767 observations is still sufficiently large for rendering the $O(I^{-4})$ error term from Equation (A.18) ignorable for my purposes. Hence, in what follows, I will use Equation (A.17) to represent the conditional expectation of the future employment share.

Explicit Expression for True Aggregate Cleansing Effect. We are now in position to write the explicit expression for the true aggregate cleansing effect:

$$\mathbb{C}_{t,t+h} = \sum_{i=1}^{I} \left\{ \frac{L_{i,t}(1 + \beta_{1,h} a_{i,t})}{\sum\limits_{i=1}^{I} L_{i,t}(1 + \beta_{1,h} a_{i,t})} a_{i,t} \right\} - \sum_{i=1}^{I} w_{i,t} a_{i,t} = \tag{A.19}$$

$$\frac{\sum\limits_{i=1}^{I} a_{i,t} L_{i,t} + \sum\limits_{i=1}^{I} \beta_{1,h} a_{i,t}^2 L_{i,t}}{\sum\limits_{i=1}^{I} L_{i,t} + \sum\limits_{i=1}^{I} \beta_{1,h} a_{i,t} L_{i,t}} - \sum_{i=1}^{I} w_{i,t} a_{i,t} = \frac{\sum\limits_{i=1}^{I} a_{i,t} L_{i,t} + \sum\limits_{i=1}^{I} \beta_{1,h} a_{i,t}^2 L_{i,t}}{\sum\limits_{i=1}^{I} L_{i,t} + \sum\limits_{i=1}^{I} \beta_{1,h} a_{i,t} L_{i,t}} - \frac{\sum\limits_{i=1}^{I} a_{i,t} L_{i,t}}{\sum\limits_{i=1}^{I} L_{i,t}}.$$

A.4.2 Estimated Aggregate Cleansing Effect

Explicit Expression for Estimated Aggregate Cleansing Effect. As explained in Section 4.3, my estimate of the aggregate cleansing effect, which I denote by $\hat{\mathbb{C}}_{t,t+h}$, is given by

$$\hat{\mathbb{C}}_{t,t+h} = \sum_{i=1}^{I} \left\{ \frac{L_{i,t}(1+\hat{\delta}_h \hat{u}_{i,t})}{\sum_{i=1}^{I} L_{i,t}(1+\hat{\delta}_h \hat{u}_{i,t})} \hat{u}_{i,t} \right\} - \sum_{i=1}^{I} w_{i,t}\hat{u}_{i,t} = \tag{A.20}$$

$$\frac{\sum_{i=1}^{I} \hat{u}_{i,t}L_{i,t} + \sum_{i=1}^{I} \hat{\delta}_h \hat{u}_{i,t}^2 L_{i,t}}{\sum_{i=1}^{I} L_{i,t} + \sum_{i=1}^{I} \hat{\delta}_h \hat{u}_{i,t} L_{i,t}} - \sum_{i=1}^{I} w_{i,t}a_{i,t} = \frac{\sum_{i=1}^{I} \hat{u}_{i,t}L_{i,t} + \sum_{i=1}^{I} \hat{\delta}_h \hat{u}_{i,t}^2 L_{i,t}}{\sum_{i=1}^{I} L_{i,t} + \sum_{i=1}^{I} \hat{\delta}_h \hat{u}_{i,t} L_{i,t}} - \frac{\sum_{i=1}^{I} \hat{u}_{i,t}L_{i,t}}{\sum_{i=1}^{I} L_{i,t}},$$

where $\hat{u}_{i,t}$ is the i'th row of $\hat{u}_{\mathbf{I},t} = \psi a_{\mathbf{I},t} - \psi X_{\mathbf{I},t}(X'_{\mathbf{I},t}X_{\mathbf{I},t})^{-1}X'_{\mathbf{I},t}a_{\mathbf{I},t}$.

A.4.3 Underestimation of True Aggregate Cleansing Effect

It is in general not possible to obtain analytical results regarding the asymptotic size of $\hat{\mathbb{C}}_{t,t+h}$ relative to its true counterpart $\mathbb{C}_{t,t+h}$. However, it is possible to show through appropriate simulations that, conditional on my observed sample and related coefficient estimates, there is a meaningful underestimation of the true aggregate cleansing effect, i.e., $\mathbb{C}_{t,t+h} \geq \hat{\mathbb{C}}_{t,t+h}$. This what I turn to show in the remainder of this section.

Substituting Out $\hat{\delta}_h$ and $\hat{u}_{i,t}$ From Equation (A.20). Considering that my sample size is sufficiently large for the asymptotic relations $\hat{\delta}_h = \frac{\beta_{1,h}}{\psi}$ and $\hat{u}_{i,t} = \psi\tilde{a}_{i,t}$ to hold with sufficient precision for my observed sample and associated estimates, we can use these relations to substitute out $\hat{\delta}_h$ and $\hat{u}_{i,t}$ from Equation (A.20) and obtain the following expression for $\hat{\mathbb{C}}_{t,t+h}$:

$$\hat{\mathbb{C}}_{t,t+h} = \frac{\sum_{i=1}^{I} \psi\tilde{a}_{i,t}L_{i,t} + \sum_{i=1}^{I} \beta_{1,h}\psi\tilde{a}_{i,t}^2 L_{i,t}}{\sum_{i=1}^{I} L_{i,t} + \sum_{i=1}^{I} \beta_{1,h}\tilde{a}_{i,t} L_{i,t}} - \frac{\sum_{i=1}^{I} \psi\tilde{a}_{i,t}L_{i,t}}{\sum_{i=1}^{I} L_{i,t}}. \tag{A.21}$$

Simulation Experiment. To asses the size of $\mathbb{C}_{t,t+h}$ relative to that of $\hat{\mathbb{C}}_{t,t+h}$ (i.e., the magnitude of underestimation), I form a grid of ψ that ranges between 0.5 and 1 with spacing of 0.01 and use my empirical estimates of $\hat{\delta}_h$ and $\hat{u}_{i,t}$ to compute the values of $\beta_{1,h}$ and $\tilde{a}_{i,t}$ for each value of ψ's grid.[33] This allows me to compute $\hat{\mathbb{C}}_{t,t+h}$ from Equation (A.21) for each value in this grid.

To correspondingly compute $\mathbb{C}_{t,t+h}$ from Equation (A.19) for each value of ψ's grid, I need values for $a_{i,t}$. Toward this end, I randomly generate $a_{i,t}$ for each value of ψ's grid as follows. Let $r_{i,t}$ be a uniformly distributed random (white noise) variable with lower and upper bounds of zero and $s\tilde{a}_{i,t}$, respectively, where s is a scale parameter whose role will be discussed below. Then, if $\tilde{a}_{i,t} > 0$, I generate $a_{i,t}$ as the sum of $\tilde{a}_{i,t}$ and $r_{i,t}$; and if $\tilde{a}_{i,t} < 0$, I generate $a_{i,t}$ as the difference between $\tilde{a}_{i,t}$ and $r_{i,t}$. This way of simulating $a_{i,t}$ implies that, for all i, when $s > 0$ then $\tilde{a}_{i,t} < a_{i,t}$; when $s = 0$ then $\tilde{a}_{i,t} = a_{i,t}$; and when $s < 0$ then $\tilde{a}_{i,t} < a_{i,t}$.

Recall that $\tilde{a}_{i,t}$ is the residual obtained from regressing $a_{i,t}$ on labor and capital inputs. Hence, the case of $s < 0$ corresponds to a downward bias in the OLS coefficients on the latter inputs; the case of $s = 0$ corresponds to no bias in them; and the case of $s > 0$ corresponds to an upward bias in them. While the upward bias case is in general both theory- and data-consistent,[34] I wish to purse an agnostic approach and establish that my estimation approach underestimates the true aggregate cleansing effects for all of these three bias direction cases.

To ensure that my results are not driven by any one particular randomly drawn series of $r_{i,t}$, I repeat the simulation described above 1000 times collecting for each simulation the difference (in percentage terms) between the true and estimated aggregate cleansing effects (i.e., $\frac{\mathbb{C}_{t,t+h} - \hat{\mathbb{C}}_{t,t+h}}{\hat{\mathbb{C}}_{t,t+h}}$) for each value of ψ's grid, and compute the median, maximal, and minimal values for this object across the 1000 replications.[35] I do this for $s = -0.5$, $s = 0$, and $s = 0.5$, i.e., for the case of $a_{i,t}$ being smaller than $\tilde{a}_{i,t}$ on average by 25%; for the case of $\tilde{a}_{i,t} = a_{i,t}$; and for the case of $a_{i,t}$ being greater than $\tilde{a}_{i,t}$ on average by 25%.

[33] For simplicity, I assume a common ψ for all industries in my sample. The message of my simulation experiment is qualitatively unchanged, and in fact is materially amplified in quantitative terms, when ψ is allowed to take on smaller values than 0.5. However, as noted by Decker et al. (2020), a standard value for ψ from the literature (which they also use in the calibration of their model) is 0.67. Hence, I allow for a reasonable range of values for ψ around this standard value.

[34] This statement is made on the basis of the fact that such upward bias is rooted in there being positive cross-sectional correlation between TFP and labor and capital inputs, and this positive correlation is borne out by the literature's robust evidence on a positive covariance between productivity and size (see, e.g., Bartelsman et al. (2013)).

[35] Note that $\hat{\mathbb{C}}_{t,t+h}$ does not change across replications, being always equal to the estimated aggregate cleansing effect.

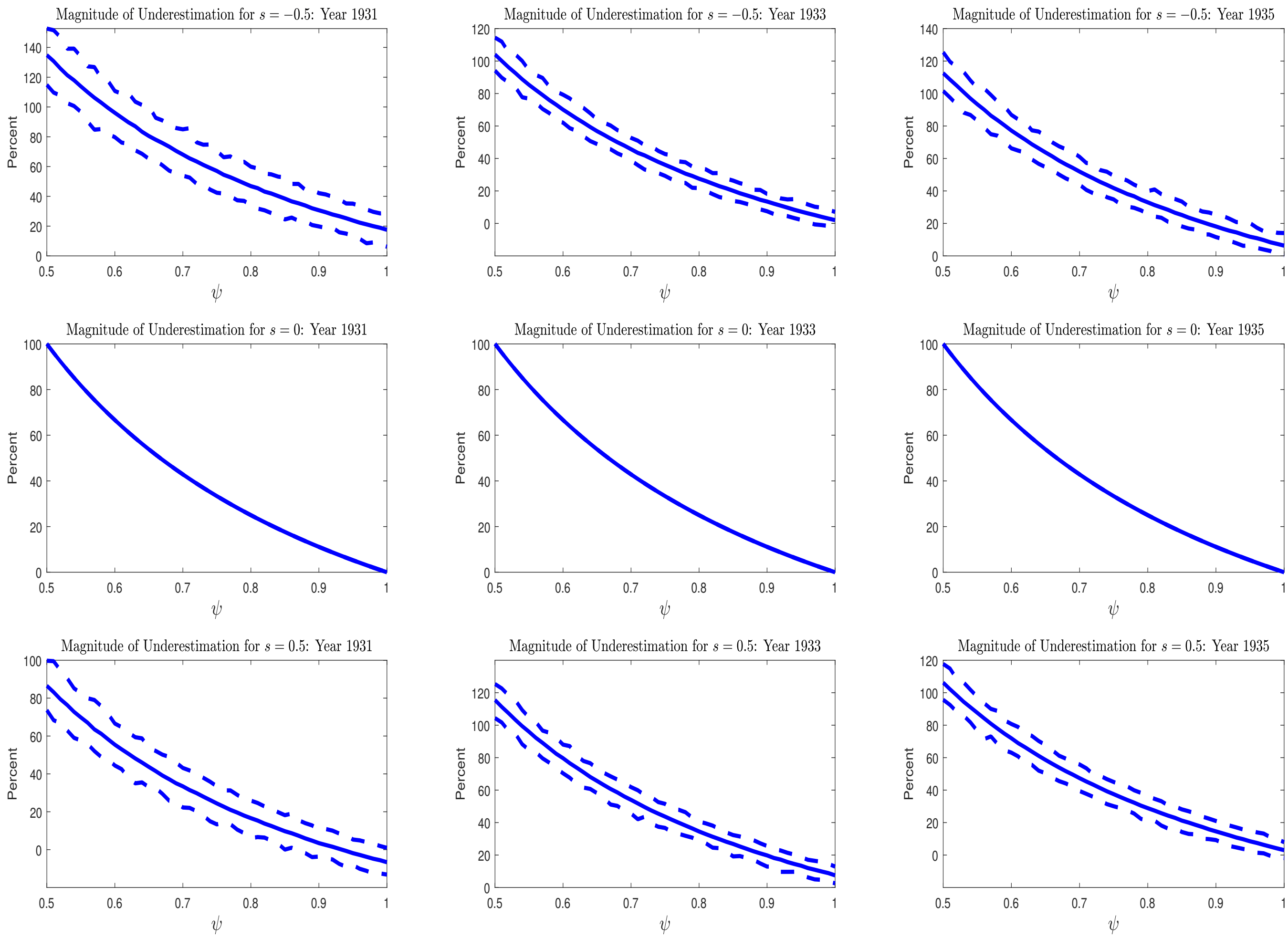
Simulation Results. Figure A.1 shows $\frac{\mathbb{C}_{t,t+h}-\hat{\mathbb{C}}_{t,t+h}}{\hat{\mathbb{C}}_{t,t+h}}$ for each value of ψ's grid. This figure contains a total of nine sub-figures, with each column corresponding to a different h ($h = 2,4,6$ corresponding to 1931, 1933, and 1935 related estimates) and each row corresponding to a different s ($s = -0.5, 0, 0.5$). (These results pertain to the continuers and exiters sample. Similar results obtain for the only continuers sample.) Solid lines depict the median underestimation magnitude across replications while the lower and upper dashed lines represent the minimal and maximal underestimation magnitudes across replications.

The results from Figure A.1 clearly indicate the robust nature of my estimation approach's underestimation of the true aggregate cleansing effect, with the true aggregate cleansing effect *never* being meaningfully below its estimated counterpart while being considerably above it for effectively all ψ values. The one exception is extreme ψ values approaching $\psi = 1$ (i.e., establishments facing perfectly elastic output demand) for the $s > 0$ case and only 1931. But even for this very particular setting the median true aggregate cleansing effect is only modestly lower than its estimated counterpart, with the gap beginning to be negative from $\psi = 0.94$ onward and troughing at -6.6% for $\psi = 1$. It is noteworthy that for the $s = 0$ case there is no bias in the estimation when $\psi = 1$. In general, $s = 0$ induces determinism in the simulation experiment thus resulting in identical median, maximal, and minimal underestimation biases, since it implies that $\frac{\mathbb{C}_{t,t+h}-\hat{\mathbb{C}}_{t,t+h}}{\hat{\mathbb{C}}_{t,t+h}} = \psi^{-1} - 1$ (which becomes zero when $\psi = 1$).

Taking the standard value of $\psi = 0.67$ as a benchmark (Decker et al. (2020)), we can see that the magnitude of underestimation is in the order of 39%-76% across years and s values (i.e., the median true aggregate cleansing effect is 39%-76% higher than its estimated counterpart). And the minimal values of this underestimation across replications (i.e., the lower (dashed) bands in the sub-figures corresponding to $\psi = 0.67$) are never below 29.5%. The more realistic case of $s > 0$ produces a severe underestimation of 39.1%, 60.7%, and 53.9% for 1931, 1933, and 1935, respectively. (The less realistic cases of $s < 0$ and $s = 0$ produce even moderately greater underestimation.)

In sum, the main takeaway from this section is that my estimated aggregate cleansing effect materially underestimates its true counterpart. I have obtained this underestimation result in an agnostic manner, solely relying on my observed sample of initial (1929) employment levels along with the estimated micro-level cleansing effect and associated residual from Regression (13). We can therefore be fairly confident in the validity of this paper's message about the Great Depression period being a period of great cleansing.

Figure A.1: **Underestimation of True Aggregate Cleansing Effect.**



Notes: This figure presents the results from the simulation experiment described in Appendix A.4.3. The figure shows $\frac{c_{t,t+h}-\hat{c}_{t,t+h}}{\hat{c}_{t,t+h}}$ for each value of ψ's grid. Solid, lower dashed, and upper dashed lines depict the median, minimal, and maximal underestimation magnitudes across replications. Each column of the figure corresponds to a different h ($h = 2, 4, 6$ corresponding to 1931, 1933, and 1935 related estimates) and each row corresponds to a different scale parameter s ($s = -0.5, 0, 0.5$). $s = -0.5$ ($s = 0.5$) corresponds to $a_{i,t}$ being smaller (greater) than $\tilde{a}_{i,t}$ on average by 25% whereas $s = 0$ corresponds to $a_{i,t} = \tilde{a}_{i,t}$. The results pertain to the continuers and exiters sample. The x-axis shows a grid of ψ (where $\frac{1}{\psi-1}$ is the price elasticity of output demand (see Equation (4) from the text)) from 0.5 to 1 with a spacing of 0.01. Y-axis shows the magnitude of underestimation in percentage terms (i.e., $100\frac{c_{t,t+h}-\hat{c}_{t,t+h}}{\hat{c}_{t,t+h}}$).

Appendix B Posterior Distribution of Parameters for Micro-Level and Bottom-Up Estimations

Since the Bayesian estimation of Equations (12) and (13) is done sequentially, estimating the latter conditional on that of the former, I present here the estimation for each equation separately while taking as given the estimated posterior draw of the residual series from Equation (12) when estimating Equation (13).

Estimation of Equation (12). Drawing on the notation from Page 19, let the set of the parameters (coefficients matrix and residual standard deviation) to be estimated from Equation (12) be given by $\mathbb{A}$ and σ_1. Equation (12) can then be written in companion form as follows:

$$Y_1 = X_1\mathbb{A} + \zeta_1, \tag{B.1}$$

where $Y_1 = [y_0, y_1, ..., y_I]'$; $X_1 = [D_{0,ind}, ..., D_{I,ind}; D_{0,county}, ..., D_{I,county}; l_0, ..., l_I; k_0, ..., k_I]'$, with $D_{i,ind}$ and $D_{i,mp}$ being the industry and county fixed effects, respectively; $\mathbb{A} = [\gamma_{ind,h}, \gamma_{county,h}, \gamma_1, \gamma_2]'$; and $\zeta_1 = [u_0, u_1, ..., u_I]'$. $\mathbb{A}$ here represents the coefficient matrix of Equation (12) and σ_1^2 is the variance of $u_{i,h}$. i indexes establishments, with $i = 1, ..., I = 17,767$ ($I = 17,767$ is the number of establishments in the sample).

I assume the following normal-inverse Wishart prior distribution for these parameters:

$$vec(\mathbb{A}) \mid \sigma_1^2 \sim N(vec(\bar{\mathbb{A}}_0), \sigma_1^2 \times N_0^{-1}), \tag{B.2}$$

$$\sigma_1^2 \sim IW(v_0 S_0, v_0), \tag{B.3}$$

where $\bar{\mathbb{A}}_0$ is an arbitrary matrix with the same size as $\mathbb{A}$; N_0 is a positive definite matrix; S_0 is a variance scalar; and $v_o > 0$. It is well known that the latter prior implies the following posterior distribution:

$$vec(\mathbb{A}) \mid \sigma_1^2 \sim N(vec(\bar{\mathbb{A}}), \sigma_1^2 \times N^{-1}), \tag{B.4}$$

$$\sigma_h^2 \sim IW(vS, v), \tag{B.5}$$

where $v = I + v_0$; $N = N_0 + X_1'X_1$; $\bar{\mathbb{A}} = N^{-1}(N_0\bar{\mathbb{A}}_0 + X_1'X_1\hat{\mathbb{A}})$; $S = \frac{v_0}{v}S_0 + \frac{I}{v}\hat{\sigma}_1^2 + \frac{1}{v}(\hat{\mathbb{A}} - \bar{\mathbb{A}}_0)'N_0N^{-1}X_1'X_1(\hat{\mathbb{A}} - \bar{\mathbb{A}}_0)$, where $\hat{\mathbb{A}} = (X_1'X_1)^{-1}(X_1)'Y_1$ and $\hat{\sigma}_1^2 = (Y_1 - X_1\hat{\mathbb{A}})'(Y_1 - X_1\hat{\mathbb{A}})/I$.

I use a weak prior, i.e., $v_0 = 0$, $N_0 = 0$, and arbitrary S_0 and $\bar{\mathbb{A}}_0$. This implies that the prior distribution is proportional to σ_1^2 and that $v = I$, $S = \hat{\sigma}_1^2$, $\bar{\mathbb{A}} = \hat{\mathbb{A}}$, and $N = X_1' X_1$. Due to the within-industry correlation of the error term u_i, the likelihood function is misspecified which in turn requires that the residual variance estimate $\hat{\sigma}_1^2$ be appropriately modified so as to improve estimation precision (Müller (2013)). Toward this end, I apply a correction to $\hat{\sigma}_1^2$ which clusters the standard errors at the industry level and denote the corrected variance estimate by $\hat{\sigma}_{1,clus}^2$.

We are now in position to lay out the posterior simulator for $\mathbb{A}$ and σ_1^2, which can be described as follows:

1. Draw σ_1^2 from an $IW(I\hat{\sigma}_{1,clus}^2, I)$ distribution.

2. Draw $\mathbb{A}$ from the conditional distribution $MN(\hat{\mathbb{A}}, \sigma_1^2 \times (X_1' X_1)^{-1})$.

3. Repeat Steps 1-3 a large number of times and collect the drawn $\mathbb{A}$'s and σ_1^2's.

Once I have these draws at hand, I compute the residual from Equation (12) (i.e., $\hat{u}_i$) and feed it into the estimation of Equation (13),[36] as described next.

Estimation of Equation (13). Continuing to draw on the notation from Page 19, let the set of the parameters (coefficients matrix and residual standard deviation) to be estimated from Equation (13) be given by B_h and $\sigma_{2,h}$. Equation (13) can then be written in companion form as follows:

$$Y_{2,h} = X_2 B_h + \zeta_{2,h} \tag{B.6}$$

h is the regression's horizon with $h = 2, 4, 6$ corresponding to years 1931, 1933, and 1935; $Y_{2,h} = [g_{0,h}, g_{1,h}, ..., g_{I,h}]'$; $X_2 = [D_{0,mp}, ..., D_{I,mp}; \hat{u}_0, ..., \hat{u}_I]'$, where $D_{i,mp}$ are the multi-establishment firm fixed effects; $B_h = [\gamma_{me,h}, \delta_h]'$; and $\zeta_{2,h} = [v_{0,h}, v_{1,h}, ..., v_{I,h}]'$. B_h here represents the coefficient matrix of Equation (13) and $\sigma_{2,h}^2$ is the variance of $v_{i,h}$.

I assume the following normal-inverse Wishart prior distribution for these parameters:

$$vec(B_h) \mid \sigma_{2,h}^2 \sim N(vec(\bar{B}_{0,h}), \sigma_{2,h}^2 \times N_0^{-1}), \tag{B.7}$$

$$\sigma_{2,h}^2 \sim IW(v_0 S_{0,h}, v_0), \tag{B.8}$$

[36]When I report the results on the micro-level cleansing effect, I refer to a unit standard deviation effect by dividing each posterior draw of the coefficient $\hat{\delta}_h$ by $\hat{u}_i$'s standard deviation $\sqrt{\sigma_1}$.

where $\bar{B}_h^0$ is an arbitrary matrix with the same size as B_h; N_0 is a positive definite matrix; S_0 is a variance scalar; and $v_o > 0$. The latter prior implies the following posterior distribution:

$$vec(B_h) \mid \sigma_{2,h}^2 \sim N(vec(\bar{B}_h), \sigma_{2,h}^2 \times N^{-1}), \tag{B.9}$$

$$\sigma_{2,h}^2 \sim IW_k(v_h S_h, v_h), \tag{B.10}$$

where $v_h = I + v_0$; $N = N_0 + X_2' X_2$; $\bar{B}_h = N^{-1}(N_0 \bar{B}_h^0 + X_2' X_2 \hat{B}_h)$; $S_h = \frac{v_0}{v} S_{0,h} + \frac{I}{v_h}\hat{\sigma}_{2,h}^2 + \frac{1}{v_h}(\hat{B}_h - \bar{B}_{0,h})' N_0 N^{-1} X_2' X_2 (\hat{B}_h - \bar{B}_{0,h})$, where $\hat{B}_h = (X_2' X_2)^{-1} (X_2)' Y_{2,h}$ and $\hat{\sigma}_{2,h}^2 = (Y_{2,h} - X_2 \hat{B}_h)'(Y_{2,h} - X_2 \hat{B}_h)/I$.

I use a weak prior, i.e., $v_0 = 0$, $N_0 = 0$, and arbitrary $S_{0,h}$ and $\bar{B}_{0,h}$. This implies that the prior distribution is proportional to $\sigma_{2,h}^2$ and that $v_h = I$, $S_h = \hat{\sigma}_{2,h}^2$, $\bar{B}_h = \hat{B}_h$, and $N = X_2' X_2$. Due to the within-industry correlation of the error term $v_{i,h}$, the likelihood function is misspecified which in turn requires that the residual variance estimate $\hat{\sigma}_{2,h}^2$ be appropriately modified so as to improve estimation precision (Müller (2013)). Toward this end, as in the estimation of Equation (12), I apply a correction to $\hat{\sigma}_{2,h}^2$ which clusters the standard errors at the industry level and denote the corrected variance estimate by $\hat{\sigma}_{2,h,clus}^2$.

We are now in position to lay out the posterior simulator for B_h and $\sigma_{2,h}^2$, which can be described as follows:

1. Draw $\sigma_{2,h}^2$ from an $IW(I\hat{\sigma}_{2,h,clus}^2, I)$ distribution.

2. Draw B_h from the conditional distribution $MN(\hat{B}_h, \sigma_{2,h}^2 \times (X_2' X_2)^{-1})$.

3. Repeat Steps 1-3 a large number of times and collect the drawn B_h's and $\sigma_{2,h}^2$'s.

Estimation of Cleansing-Induced Aggregate TFP Change. The posterior draws of $\hat{u}_i$ and $\hat{\delta}_h$ can be used to construct the posterior distribution of $\mathbb{C}_h$ from the aggregate cleansing effect formula from Equation (14). In particular, I compute $\hat{g}_{i,h} = \hat{\delta}_h \hat{u}_i$ and then use this predicted value to generate the predicted employment share in period $1929 + h$, i.e., $\hat{w}_{i,h} = \frac{L_i(1+\hat{g}_{i,h})}{\sum_{i=1}^{I} L_i(1+\hat{g}_{i,h})}$ where $\hat{w}_{i,h}$ is establishment i's predicted employment share for year $1929 + h$ and L_i is establishment i's employment in 1929. I then use these predicted employment share weights to compute the posterior draw of $\hat{\mathbb{C}}_h$ from the aggregate cleansing effect formula from Equation (14).

Accordingly, the posterior simulator for $\mathbb{C}_h$ can be described as follows:

1. Do Steps 1 and 2 from the posterior simulator of Equation (12) and obtain a posterior draw of $\hat{u}_i$.

2. Using the latter $\hat{u}_i$ value, do Steps 1 and 2 from the posterior simulator of Equation (13) and obtain a posterior draw of $\hat{\delta}_h$.

3. Compute predicted employment growth as $\hat{g}_{i,h} = \hat{\delta}_h \hat{u}_i$.

4. Compute predicted employment share in period $1929 + h$ as $\hat{w}_{i,h} = \frac{L_i(1+\hat{g}_{i,h})}{\sum_{i=1}^{I} L_i(1+\hat{g}_{i,h})}$.

5. Insert $\hat{w}_{i,h}$ into Equation (14) and obtain $\hat{\mathbb{C}}_h$.

6. Repeat Steps 1-5 a large number of times and collect the drawn $\mathbb{C}_h$.

Appendix C Robustness Checks

This appendix examines the robustness of the baseline results for $\hat{\delta}_h$ and $\hat{\mathbb{C}}_h$ along three dimensions. The first considers an alternative formulation of the production structure from Section 3.1 which removes the Leontief production structure assumption and allows the intermediate input factor to be substitutable for the other input factors. The second deals with the issue of cross-sectional variation in input utilization. And the third concerns the application of the two-way standard error clustering approach from Cameron et al. (2011) to my setting, extending my baseline one-way clustering at the industry level to also allow for error dependence within states (in addition to within industries).

C.1 Alternative Production Structure

The underlying framework of the baseline empirical analysis assumes a Leontief production structure where physical intermediate inputs $M_{i,t}$ have no substitutability and are linearly related to physical output $Z_{i,t}$. An alternative production structure that allows for such substitutability can be represented by the following production function (which replaces that from Equation (2)):

$$Z_{i,t} = A_{i,t} L_{i,t}^{\alpha_L} K_{i,t}^{\alpha_K} M_{i,t}^{\alpha_M}, \tag{C.1}$$

where now physical intermediate input enters the production function with intermediate input share α_M. This alternative representation for physical output requires the addition of a measure of *physical* intermediate inputs as explanatory variable in Regression (12). To account for physical intermediate input under the alternative production structure from Equation (C.1), I make use of available data from the COM on electricity usage in kilowatt hour (kWh) units (from both purchased and generated electricity).[37] This variable was only collected in the 1929 COM, which is suitable for my purposes given that 1929 is my year of interest for estimating initial TFP. And it is available for 17,097 establishments, a moderately smaller sample size than the baseline sample size.

The results from adding logged electricity usage to Regression (12) as an explanatory variable appear in Figure C.1. It is clear that accounting for the alternative production structure from Equation (C.1) has no meaningful quantitative bearing on the results. The results from Figure C.1 are similar to those from Figure 2 and lend further support to the notion that considerable cleansing took place in the Great Depression period at hand.

C.2 Cross-Sectional Variation in Input Utilization

My baseline Regression (12) as well as its underlying production structure implicitly assumes away cross-sectional variation in unobserved input utilization. This raises the concern that the residual estimated from Regression (12) picks up cross-sectional variation in the extent to which labor and capital inputs are utilized. Unfortunately, given the essentially null time dimension of my data, it is beyond the scope of this paper to account for varying utilization of factor inputs in the estimation of Regression (12) along the lines of the time series instrumental variable approach from Basu et al. (2006) (also see related discussion on Page 16).

Nevertheless, the COM asked respondents in 1929 to report the number of weekly hours for

[37] While *nominal* values for intermediate inputs (cost of raw materials, fuels, and purchased electric energy) are available from the COM, using them to proxy for physical intermediate input would induce a bias because of likely heterogeneity in the prices of these inputs. See Atalay (2014) for evidence from modern U.S. establishment-level manufacturing data on substantial within-industry variation in materials input prices facing establishments. And see Ornaghi (2006) and Grieco et al. (2016) for evidence on the substantial bias that results from estimating production functions without accounting for materials input price heterogeneity.

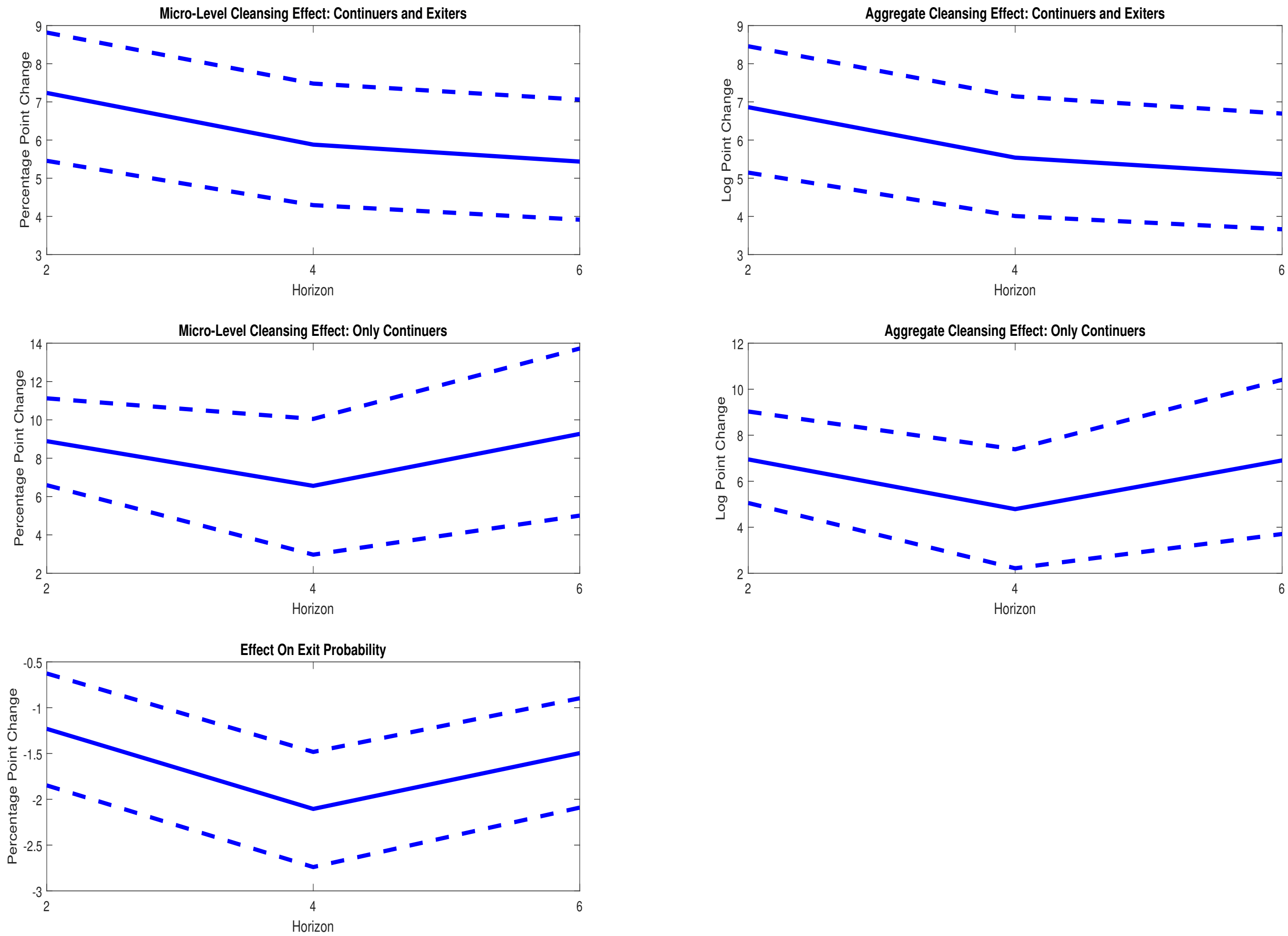
which their establishment operated. While this is an imperfect proxy for unobserved input utilization, I still view the inclusion of this variable in Regression (12) as informative for the robustness of the results to cross-sectional variation in input utilization. Figure C.2 presents the results from adding the log of my input utilization proxy as an additional explanatory variable in Regression (12). (This variable is available for 17,745 establishments, only slightly less than the 17,767 baseline sample.) The results from Figure C.2 allay the concern that cross-sectional variation in unobserved input utilization is driving this paper's results as the addition of my utilization measure to Regression (12) produces similar results to the baseline ones.

C.3 Two-Way Clustered Standard Errors

In my baseline estimation, as explained in Appendix B, I apply a correction to standard errors which clusters them at the industry level (this is done in both stages of the estimation). One may argue that a more suitable clustering approach is ones that takes into account possible dependence of errors within counties in addition to within industries. Toward this end, I repeat my baseline estimate procedure and replace my one-way clustering approach with the two-way clustering approach from Cameron et al. (2011) which clusters at both the industry and the state level. (It is noteworthy that the resulting standard error from such two-way clustering need not necessarily be greater than the one-way clustered standard error since the former is equal to square root of the sum of the variances clustered by each group *minus* the variance from the intersected clusters.)

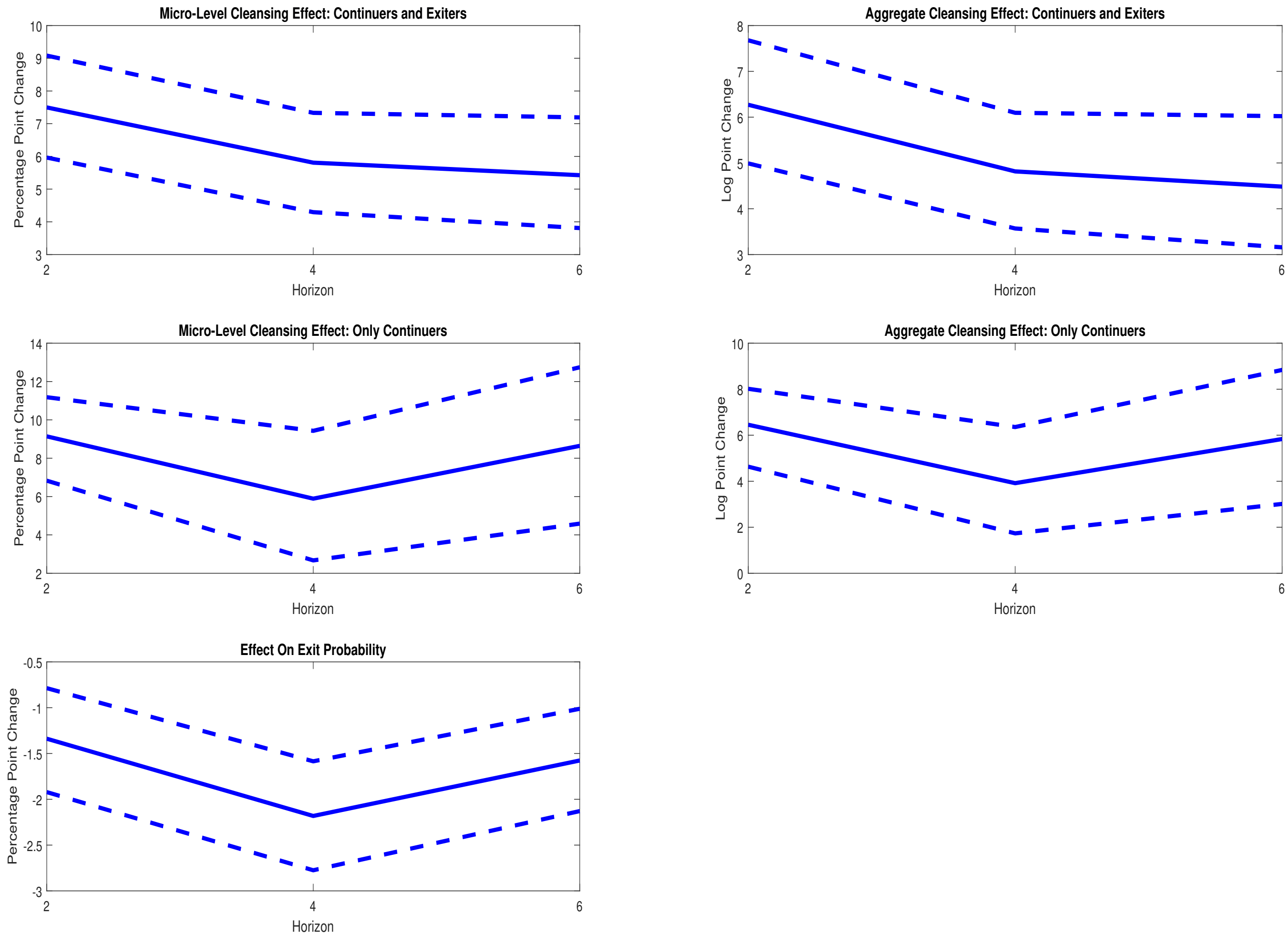
The results from this estimation exercise appear in Figure C.3. It is evident that the statistical significance of the baseline estimates is not affected by the use of the alternative two-way clustering approach. The posterior bands from Figure C.3 are comparable in size to those from baseline Figure 2, continuing to support this paper's main message about a substantial aggregate cleansing effect taking place in the Great Depression period at hand.

Figure C.1: **Alternative Production Structure: Cleansing-Induced Effect.**



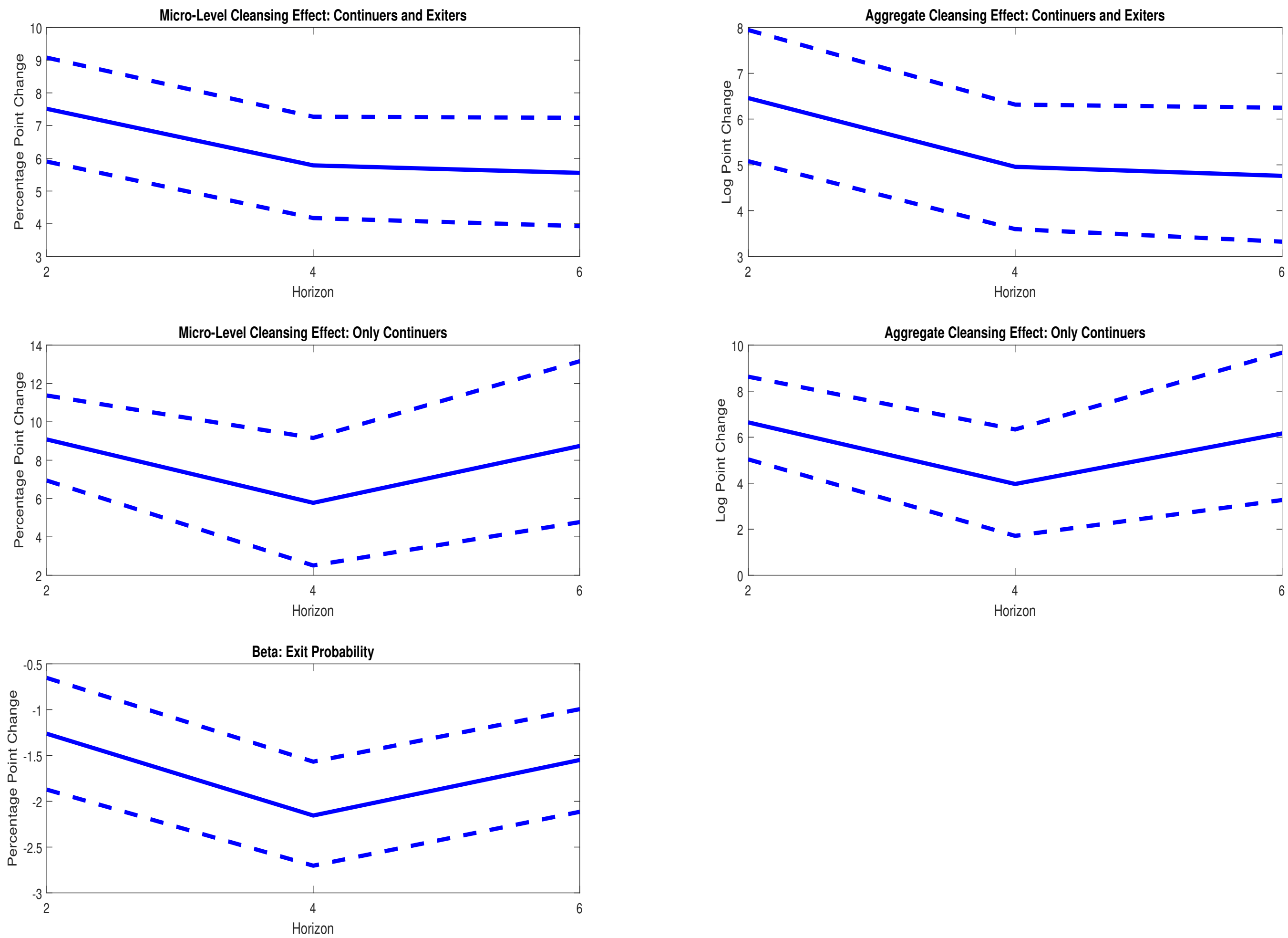
Notes: This figure's exposition is identical to that of baseline Figure 2, only that now logged electricity usage (in Kwh units) is added to Regression (12) to account for the alterative production structure from Equation (C.1) (which replaces that from Equation (2)).

Figure C.2: **Accounting for Input Utilization: Cleansing-Induced Effect.**



Notes: This figure's exposition is identical to that of baseline Figure 2, only that now the log of number of weekly hours for which the establishment operated is added to Regression (12) to account for cross-sectional variation in unobserved input utilization.

Figure C.3: **Two-Way Clustering Approach: Cleansing-Induced Effect.**



Notes: This figure's exposition is identical to that of baseline Figure 2, only that now the two-way standard error clustering approach from Cameron et al. (2011) is used (where the clustered groups are industries and states) instead of the baseline one-way clustering approach (where industries are the only group being clustered).