Essays in International Economics and Macroeconomics

by

Sui-Jade Ho

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Doctoral Committee:

Professor Andrei Levchenko, Chair
Professor Alan Deardorff
Assistant Professor Kyle Handley
Assistant Professor Sebastian Sotelo

Sui-Jade Ho

sjadeho@umich.edu

ORCID iD: 0000-0002-4678-319X

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ABSTRACT

Essays on International Economics and Macroeconomics

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Chair: Professor Andrei Levchenko

The first chapter presents a study on the employment effects of periodic policy lapses and renewals. Economic theory postulates that uncertainty and temporary disruptions in policies could lead to more permanent effects on the real economy by reducing growth and investment. The sources of policy uncertainty are manifold (Baker et al., 2014), in which political polarization is a potential explanation in the rise in policy-related economic uncertainty in the U.S.. One way in which political polarization could translate to greater policy uncertainty is the challenges involved in passing policies that are subjected to periodic lapses and retroactive renewal. This paper seeks to examine the cost of this type of policy shock on firm employment outcomes. I utilized the periodic lapses and renewals of the Generalized Systems of Preferences (GSP) in the 1990s to estimate the effects on firm

employment. Depending on the amount of imports, firms with higher dependency on the GSP regime experienced slower employment growth. The difference in the employment growth rates between the GSP firms and controls persists for about four years.

The second chapter discusses a key empirical challenge in measuring misallocation and proposes a method to resolve the identification problem. The challenge in the misallocation literature made popular by Hsieh and Klenow (2009) is the identification of model parameters: a standard implementation cannot separately identify the production function parameters from the measures of distortion. In this paper, my co-author and I formally characterize two biases related to this lack of identification: mismeasuring the labor output elasticity in a constant returns-to-scale world, and assuming constant returns to scale when returns to scale in production are not constant. In both cases, the econometrician's error induces spurious correlations between productivity and distortions, leading the econometrician to mismeasure misallocation. We first show how misallocation measures in this class of models can be identified even when we cannot identify all the model parameters. We then use U.S. Census Bureau microdata and document the magnitude of the two biases.

The third chapter measures the aggregate employment growth and reallocation effects of multinational firms in the U.S. over the past decade and across the manufacturing, retail, wholesale, and service sectors. At a fundamental level, understanding the contribution of multinational firms to U.S. employment growth in contrast to non-multinational firms is the first-order issue. Are MNCs a major component of U.S. manufacturing employment decline? Did they grow faster relative to their domestic counterparts? Did they create and destroy more jobs at new and existing establishments relative to controls? And, given that MNCs are often vertically integrated and operate multiple lines of business, in what sectors did they create and destroy jobs? My co-authors and I exploit a novel combination of two micro datasets: the restricted-use U.S. Census Bureau establishment-level microdata and the Bureau van Dyke Orbis firm database. The combined dataset links firm and establishment-level activity to the scope and extent of a firm's global operations. We find that MNCs recorded higher total employment growth rates relative to the comparison group of non-MNCs. Furthermore, MNCs create more and destroy fewer jobs than non-MNCs. Moreover, MNCs are found to have created relatively more jobs across all sectors; notably in the services sector. This result suggests that within-firm reallocation across sectors may be increasingly important in the study of business dynamism.

CHAPTER I

The Employment Effects of Periodic Policy Lapses and Renewals: Firm Level Evidence From The Generalized Systems of Preferences[1]

1.1 Introduction

Economic theory postulates that uncertainty and temporary disruptions in policies could lead to more permanent effects on the real economy by reducing growth and investment. If firms are uncertain of the timing and duration of a policy (e.g. a tax credit), then they would be more likely to adopt a wait-and-see posture before investing. As such, aggregate output growth would be slower than it would have been in the case without policy uncertainty.

The sources of policy uncertainty are manifold. Baker et al. (2014) highlight the role of the rise in political polarization in worsening policy uncertainty in the U.S.

[1]DISCLAIMER: "Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed."

over time. With the increase in political polarization comes the greater challenges involved in passing policies that are subjected to periodic lapses and retroactive renewals[2].

These periodic lapses and reinstatements in policy-making are an important area of concern because policies that are aimed to increase employment and investment could inadvertently have the opposite effects. For instance, many government credits and deductions are intended to incentivize outcomes such as investments in green energy or R&D activities. But such investments typically involve planning over the medium term and may even require substantial changes in the way in which firms operate. If the incentives are unpredictable and could potentially be abruptly revoked or suspended, then it is likely for firms to not undertake such investments in the first place. For firms that did undertake these investments, sufficiently large and protracted periods of uncertainties surrounding the relevant policy incentives could cause these firms to scale back and make divestments.

Despite conjectures that these policy uncertainty effects could be large, it is difficult to measure the micro effects on firm-level outcomes. In particular, most shocks are either aggregate in nature (e.g. government shut down) or affect all firms within an industry in the same way (e.g. wind tax credits). Therefore, it is difficult to separately identify the effects of policy lapses from the effects of other macro shocks.

In this vein, trade policy provides a particularly useful setting for us to exam-

[2]Some of these credits and deductions are known as "extenders" and are not a permanent part of the tax code. These must be periodically renewed by Congress. In December 2015, the House of Representatives passed the PATH Act which, among others, made nineteen (a third of the total) of the temporary tax provisions permanent parts of the tax code.

ine the impact of policy lapses and reinstatements. Given the broad and general nature of trade policies, the lessons that are drawn from this study are easily applicable in other contexts. First, trade transaction data contains firm-level variations across products, countries and time. Second, importers and exporters make sunk investment in import/export markets and buyer-seller relationships, as well as incur fixed costs in trade (Das et al. (2007), Halpern et al. (2015)). Third, there are sequences of well-identified policy lapses and renewals that exist in one of the U.S. trade policies; i.e. the U.S. Generalized Systems of Preferences (GSP).

Specifically, this paper seeks to examine the cost of this type of policy shock on firm employment outcomes. To do so, I analyze the impact of firms that are affected by the periodic lapses and renewals of the Generalized Systems of Preferences (GSP)[3] in the 1990s. The GSP regime is especially useful for this analysis as we are able to utilize micro-level firm data to estimate the direct effects of the policy shock.

The GSP program is a non-reciprocal trade arrangement extended by many developed countries to developing countries. Countries such as the U.S., Japan and the E.U. have similar versions of this policy in place, aimed at helping developing countries to trade internationally[4]. While the details of this policy differ for each country, the common essence is that imports from eligible trading partners are charged a lower (or zero) tariff rate relative to the prevailing Most Favored Nations (MFN) rate.

Since its inception, the U.S. GSP program has been reviewed periodically by

[3]The GSP is not part of the tax "extenders".

[4]A current review of the GSP program is provided by Jones (2015).

Congress. Throughout the 1990s, there were numerous instances in which the program was allowed to lapse; that is, Congress did not renew the program before its expiration date. When Congress eventually renewed the program, the program was extended retroactively from the date of its previous expiration. That meant that all duties that were paid during the lapsed period were subsequently refunded to importers. Nevertheless, at the point when the program lapsed, it was uncertain if the program would ever be reinstated. Moreover, the duration of the lapsed period meant that the higher amount of tariff duties paid would have important implications on the cash flow and inventory management of importers.

These periods of lapses and reinstatements provide discrete time notches of changes in tariffs that were applied in trade transactions. The removal of preference rate altered the costs of imports and if not reinstated, would directly affect firms' profits. Even if the GSP program was eventually reinstated, the impact on firms' cash flows and other firm choices, such as sourcing behavior, would likely be affected.

This study seeks to identify the effects on firm employment due to policy uncertainty, through this sequence of periodic lapses and reinstatements of the GSP policy. The GSP policy affected a relatively small number of U.S. firms, and was unlikely to change aggregate wages and prices. Therefore, using a partial equilibrium approach, this study can effectively isolate the impact of the policy shocks.

Between 1993 and 2000, the GSP regime was allowed to expire and was subsequently reinstated and extended retroactively six times (Table A.1). Although most periods of expiration were relatively short (around four and a half months on average), the disruption in July 1995 was longer and lasted for fourteen months. It is therefore reasonable to assume that the renewal of the policy as well as the timing of the renewal were both uncertain at the point of the lapse in the policy. Furthermore, it is likely for firms that were less financially constrained to be better equipped to weather the phase in which the policy lapsed. In this regard, I find that there is some evidence that the firm's financing condition could impact its employment outcomes in light of the policy shock.

This paper relates to three strands of literature. First, it provides new empirical evidence on the effects of policy uncertainty on firms' choices and outcomes (Dixit (1989), Bloom (2009), Bloom et al. (2007)) and more specifically, the effects of trade policy uncertainty (Handley (2014), Handley and Limão (2015), Ruhl (2010)). Second, this paper is also related to the literature on trade and financial constraints (Manova (2013), Manova et al. (2014), Feenstra et al. (2014)). Third, there is also a growing body of research on the GSP program (Blanchard and Hakobyan (2015), Hakobyan (2015), Hakobyan (2016)). It complements the recent work by Hakobyan (2013) that finds the 2011 expiration of the GSP regime led to the decline in the value of imports from GSP countries.

The rest of this paper is organized as follows. I first present a simple conceptual framework that provides an expression for a firm's labor demand function in the presence of changes in policy uncertainties. Then, I describe the empirical approach and the results from my estimation exercise. Next, I conduct a counterfactual exercise to estimate the aggregate effects of the policy lapses on employment. Finally, I perform a series of robustness checks of the main results, including reestimating the effects over a placebo time period, using an alternative measure of GSP usage intensity and using an alternative specification to control for unobservables at the firm level. The findings from these robustness checks are consistent with the baseline results.

1.2 Background on the U.S. Generalized System of Preferences

The GSP program is a non-reciprocal trade arrangement extended by many developed countries to developing countries. Countries such as the U.S., Japan and the E.U. have versions of this policy in place, aimed at helping developing countries to trade internationally. While the details of this policy differ for each country, the common essence is that imports from eligible trading partners are charged a lower (or zero) tariff rate relative to the prevailing Most Favored Nations (MFN) rate.

The U.S. program was established by Title V of the Trade Act of 1974. The President has the discretion to determine both country eligibility and product coverage under the GSP program[5]. In 2015, the United States Trade Representative (USTR, 2016) reported the number of GSP beneficiary countries and territories as 122, with the the total value of imports under the GSP program amounting to 17.4 billion USD (about 1 percent of total U.S. world imports). Some examples of the top GSP products (by value) include motor vehicle parts, ferroalloys, building stones, precious metal jewelry and electric motors and generators. The top GSP beneficiary countries are India, Thailand, Brazil, Indonesia and the Philippines.

[5]The actual implementation of the system; and in particular, the practice of exclusion of countries and products has been found to be subjected to extensive executive discretion (Blanchard and Hakobyan, 2015).

There are explicit criteria that determine if a country is eligible to participate in this program. These countries are designated as either beneficiary developing countries (BDC) or least-developed beneficiary countries (LBDC). Over time, several countries have graduated from the program either through the mandatory graduation criteria (that is when the BDC is determined to be a high income country as defined by the World Bank) or at the discretion of the President.

The GSP program is also used by the U.S. as a trade measure to promote worker rights. Over the years, several beneficiary countries have had their GSP privileges suspended for reasons related to worker rights concerns (e.g. Liberia in 1990, Mauritania in 1993, the Maldives in 1993, Bangladesh in 2013). While such suspensions could also contribute towards trade policy uncertainty, none of these suspensions occurred during the period of the broader GSP policy disruption in 1995–1996 that will be studied in this paper.

In terms of product coverage, the formal principle that determines product eligibility is given in the 1974 Trade Act. Of note, the GSP program excludes important import sensitive products (e.g. textiles and apparels) as a way to protect U.S. manufacturers and workers from import competition (Jones, 2015). Furthermore, the program also imposes ceilings (i.e. Competitive Need Limitations, CNL) on GSP imports for each product and beneficiary country. Upon breaching the ceilings, the GSP benefits will not be applicable and the trade transaction may be subjected to the MFN tariff rate, conditional on not passing other exception criteria. Given that the value of GSP imports is relatively small and that the GSP products are non-import sensitive, it is reasonable to consider the policy disruption in a partial equilibrium framework and abstract from its impact on aggregate wages and prices.

1.3 Conceptual Framework

The aim of this conceptual framework is to decompose the effects of a change in input cost on the elasticity of labor demand into substitution effects from higher import prices, scale effects from changes in output demand, and liquidity effects from changes in working capital requirements. The conceptual framework will combine elements of the model of incomplete exchange rates pass-through from Amiti et al. (2014) and working capital constraints from Jermann and Quadrini (2012). Under some mild assumptions, higher tariff levels on imports will be associated with lower labor demand. Furthermore, with a working capital constraint to capture the impact of liquidity constraints on the firm's labor demand, the framework will provide an additional margin in which the probability of tariff changes would impact the firm's labor demand through the liquidity constraint channel. I will first describe the model without the working capital constraints, by highlighting the interactions of the substitution and scale effects. Then, I will introduce working capital constraints into the framework.

1.3.1 Demand

Following the tradition in the incomplete pass-through literature (Atkeson and Burstein, 2008), households are assumed to have nested demand with constant-elasticity of demand at two levels of demand; i.e. at the product and variety levels[6]. Therefore, for a given variety, q_i, the demand of individual firm i is given by:

$$q_i = p_i^{-\rho} P^{\rho-\nu} D \tag{1.1}$$

where ρ is the price elasticity of demand of the variety and ν is the price elasticity of demand of the product. For an individual firm i, its market share is defined as:

$$S_i = \frac{p_i q_i}{\sum_{i'} p_{i'} q_{i'}} = \left(\frac{p_i}{P}\right)^{1-\rho}$$

where $P = \left(\sum_i p_i^{1-\rho}\right)^{1/(1-\rho)}$ is the price index of the product.

As shown in previous studies, under Bertrand competition, the effective demand elasticity is given as $\sigma_i = \rho(1-S_i)+\nu S_i$ and we can express the multiplicative markup as $\mathcal{M}_i = \sigma_i/(\sigma_i - 1)$ [7].

1.3.2 Production

On the production side, the firm's output is produced using a constant returns-to-scale Cobb-Douglas production function with two inputs; i.e. labor L_i and an intermediate input bundle X_i. The intermediate input bundle X_i is a composite of domestic intermediate varieties, Z_{ij}, and foreign intermediate varieties, M_{ijk},

[6]This demand system has previously been studied by Helpman and Krugman (1985) and others.

[7]Amiti et al. (2014) define the elasticity of markup with respect to price Γ_i as:

$$\Gamma_i = -\frac{\partial \log \mathcal{M}_\rangle}{\partial \log p_i} = \frac{S_i}{(\frac{\rho}{\rho-\nu} - S_i)(1 - \frac{\rho-\nu}{\rho-1} S_i)} > 0\ .$$

where j indexes the variety and k indexes the source country. Firms are price-takers in the input markets. The price of labor, domestic and foreign intermediates are w, V_j and U_{jk}, respectively. Foreign intermediates are also subjected to a import tariff of $\tau_{jk} \geq 0$. The firm's cost minimization problem can be written as follows:

$$\min_{L_i, Z_{ij}, Mijk} \quad wL_i + \int_0^1 V_j Z_{ij} dj + \int_J \sum_k U_{jk}(1+\tau_{jk}) M_{ijk} dj \tag{1.2}$$

s.t.

$$Y_i = \Omega_i L_i^{1-\phi} X_i^{\phi} \ , \tag{1.3}$$

$$X_i = \exp\left(\int_0^1 \gamma_j \log X_{ij} dj\right) \ , \text{ and} \tag{1.4}$$

$$X_{ij} = \left(Z_{ij}^{\epsilon/(1+\epsilon)} + \sum_k M_{ijk}^{\epsilon/(1+\epsilon)} \right)^{(1+\epsilon)/\epsilon} . \tag{1.5}$$

The full derivation of the model is in Appendix A.2. The expression for the firm's marginal cost is given as:

$$
\begin{aligned}
MC_i = \lambda = & \quad \frac{1}{\Omega_i}\left(\frac{w}{1-\phi}\right)^{1-\phi}\left(\frac{\exp\int_0^1 \gamma_j \log(\frac{V_j}{\gamma_j})dj}{\phi}\right)^{\phi}\left(\frac{1}{\exp\int_0^1 \gamma_j \log A_j^{1/\epsilon} dj}\right)^{\phi} \\
= & \quad \frac{C_i}{\Omega_i B_i^{\phi}} \qquad (1.6) \\
\text{where} \qquad C_i = & \quad \left(\frac{w}{1-\phi}\right)^{1-\phi}\left(\frac{\exp\int_0^1 \gamma_j \log(\frac{V_j}{\gamma_j})dj}{\phi}\right)^{\phi}, \\
A_j \equiv & \; 1 + \left(\frac{V_j}{\tilde{U}_j^*}\right)^{\epsilon} \\
\text{and} \qquad B_i = & \; \exp\int_0^1 \gamma_j \log A_j^{1/\epsilon} dj \; .
\end{aligned}
$$

The expression for the firm's import intensity from country k is given by

$$
\psi_k = \frac{\int_{J_0} \tilde{U}_{jk} M_{jk} dj}{\lambda Y} = \frac{\phi}{A_j}\int_{J_0} \gamma_j (\frac{\tilde{U}_{jk}}{V_j})^{-\epsilon} dj \; . \qquad (1.7)
$$

1.3.3 Elasticity of Labor Demand

The goal of this section is to obtain an expression for the firm's elasticity of labor demand. From the first order condition for labor, the firm's demand for labor is given by:

$$
L_i = (1-\phi) MC_i \frac{Y_i}{w}
$$

from which, by taking the natural logarithms, the elasticity of labor demand with respect to tariff costs can be derived. This consists of two components; i.e. the substitution effects and scale effects. From theory, the substitution effects would be positive because the relatively higher cost of intermediate inputs would lead to the firm's substituting away from intermediates towards labor. The scale effects could, however, be negative, because the pass-through of higher input costs to firm's output price could lead to a reduction in the demand for the firm's output.

$$\frac{\partial \log L_i}{\partial \log(1+\tau_{jk})} = \underbrace{\frac{\partial \log MC_i}{\partial \log(1+\tau_{jk})}}_{\text{Substitution effects}} + \underbrace{\frac{\partial \log Y_i}{\partial \log(1+\tau_{jk})}}_{\text{Scale effects}} \tag{1.8}$$

Proposition 1. The expression for the substitution effects is given as:

$$\frac{\partial \log MC_i}{\partial \log(1+\tau_{jk})} = \psi_k(1+\eta_{jk}) > 0 \ , \tag{1.9}$$

where $\eta_{jk} = \frac{1+\tau_{jk}}{U_{jk}} \frac{\partial U_{jk}}{\partial(1+\tau_{jk})} \geq 0$ is the tariff incidence from foreign sellers to domestic importers.

Proof in Appendix A.2.

Proposition 1 states that the substitution effects from an increase in the tariff rate would be positive and would be higher, the greater the import intensity of the firm for variety j from country k, and the greater the tariff incidence for that variety. This result is straightforward and intuitive.

Proposition 2. The expression for the scale effects is given as:

$$\frac{\partial \log q_i}{\partial \log(1+\tau_{jk})} = -\sigma_{ik}\left(1 - \frac{\Gamma_{ik}}{1+\Gamma_{ik}}S_{ik} + \frac{1}{1+\Gamma_{ik}}\psi_k(1+\eta_{jk})\right) .$$

Proof in Appendix A.2.

From Proposition 2, the sign of the scale effects from an increase in the tariff rate would be negative.

Proposition 3. The expression for the total effects is given as:

$$\frac{\partial \log L_i}{\partial \log(1+\tau_{jk})} = \psi_k(1+\eta_{jk})\left(1 - \frac{\sigma_{ik}}{1+\Gamma_{ik}}\right) - \sigma_{ik}\left(1 - \frac{\Gamma_{ik}}{1+\Gamma_{ik}}S_{ik}\right) .$$

Proof: Obtained from summing the substitution and scale effects.

Since $0 < \left(1 - \frac{\Gamma_{ik}}{1+\Gamma_{ik}}S_{ik}\right) < 1$, then $-\sigma_{ik}\left(1 - \frac{\Gamma_{ik}}{1+\Gamma_{ik}}S_{ik}\right) < 0$. For scale effects to dominate substitution effects, $\left(1 - \sigma_{ik}/(1+\Gamma_{ik})\right)$ must be less than zero. That is, $\sigma_{ik} > 1 + \Gamma_{ik}$. In other words, the elasticity of demand for firm i must be relatively higher than the firm's markup elasticity with respect to its price. ■

Next, I extend this baseline framework to capture the effects of the probabilistic changes in tariffs on a firm's labor demand. Consider an infinitely-lived firm which chooses new factor demands at each period with the goal of maximizing the net present value of its flow profits. I assume that the firm chooses the level of employment and material at the beginning of each period that will be used in production at the beginning at the next period. The effective tariff is assumed to be revealed at the beginning of the next period. In other words, the firm chooses and pays for its factors before the effective tariffs on the imported inputs are revealed.

I also introduce working capital loan requirements in the presence of imperfect contract enforcement. Firms are required to borrow an intra-period loan to cover the cash-flow mismatch between the payments for inputs made at the beginning of the period and the realization of revenue that takes place at the end of the period. The intra-period loan is repaid at the end of the period. For simplicity, I assume that there is no interest charged on this loan. The amount of working capital loan is subjected to an enforcement constraint that depends on the firm's expected equity value, which in turn, depends on the firm's expected future profitability. The effects of expected changes in future tariffs would enter into the firm's expected future profitability in the form of higher expected input costs. The working capital loan requirement, l_t for firm i is given as[8]:

$$l_t = w_t L_t + \int_0^1 V_{jt} Z_{jt} dj + \int_J U_{jkt}(1+\tau_{jkt}) M_{jkt} dj \ . \tag{1.10}$$

The firm's budget constraint is given as:

$$w_t L_t + \int_0^1 V_{jt} Z_{jt} dj + \int_J U_{jkt}(1+\tau_{jkt}) M_{jkt} dj = R(L_t, X_t) \ . \tag{1.11}$$

Combining (1.10) with (1.11), I obtain the condition that the intra-period loan l_t must be equal to the firm's revenue, $R(L_t, X_t)$.

Next, I derive the lender's enforcement constraint in an environment of imperfect contract enforcement. To prevent defaults, the amount of borrowing that the

[8]To simplify notation, the firm index i is omitted from this section onwards.

lender will make available for to firm is limited and is obtained as follows. Assume that in the event of a default, the lender would obtain a fraction θ of the (discounted) expected value of the firm's equity. Let the value of the firm when it defaults on its loan be V_D and when it does not default, V_N. I can write these terms as follows:

$$\begin{aligned} V_D = & \quad \pi_t + l_t + \beta(1-\theta)\mathbb{E}V' \\ V_N = & \pi_t + \beta\mathbb{E}V' \end{aligned}$$

Therefore, the enforcement constraint to ensure a non-default equilibrium would be to set $V_N \geq V_D$.

$$l_t \leq \quad \beta\theta\mathbb{E}V' \equiv \Theta \tag{1.12}$$

The enforcement constraint could bind when $\mathbb{E}V'$ decreases or when θ decreases. The latter is akin to a tightening of the enforcement constraint as discussed in Jermann and Quadrini (2012).

To introduce the role of the possibility of higher tariffs in subsequent periods, I follow the framework in Handley and Limão (2015) by assuming that there is a probability γ that tariff will change and $1-\gamma$ that tariff will remain unchanged in each subsequent period. Let τ be the tariff rate of the current period and τ' be the tariff rate for the next period. The Bellman equation for the firm's profit maximization problem is given as follows:

$$V(\tau) = \quad \pi_t + \beta[\underbrace{(1-\gamma)V(\tau)}_{\text{No tariff change}} + \underbrace{\gamma\mathbb{E}V(\tau')}_{\text{Tariff change}}] \ , \tag{1.13}$$

where π_t is the current period's operating profits and the second term represents the discounted expected future profits. With probability $1-\gamma$, tariff remains unchanged in the next period, and the firm's value in the next period remains at $V(\tau)$. With probability γ, tariffs could change in the next period. In that event, the firm's value is given as $\mathbb{E}V(\tau')$. I can express this last term as:

$$\begin{aligned} \mathbb{E}V(\tau') = &\quad \mathbb{E}\pi(\tau') + \beta\mathbb{E}V(\tau') \\ = &\quad \frac{\mathbb{E}\pi(\tau')}{1-\beta} \ . \end{aligned} \tag{1.14}$$

Substituting (1.14) in (1.13), I obtain the following expression for the firm's value.

$$V(\tau) = \quad \frac{1}{1-\beta(1-\gamma)}\pi_t + \frac{\beta}{1-\beta}\frac{\gamma}{1-\beta(1-\gamma)}\mathbb{E}\pi_t(\tau') \tag{1.15}$$

The firm's profit maximization problem is specified as follows:

$$\begin{aligned} V(\tau) = \quad & \max_{L,Z,M,X,X_j} \quad \frac{1}{1-\beta(1-\gamma)}\left[p_tY_t - (wL_t + \int_0^1 V_{jt}Z_{jt}dj + \int_J U_{jkt}(1+\tau_{jkt})M_{jkt}dj)\right] + \\ & \frac{\beta}{1-\beta}\frac{\gamma}{1-\beta(1-\gamma)}\mathbb{E}_t\pi_t(\tau') \end{aligned} \tag{1.16}$$

s.t.

$$
\begin{aligned}
Y_t = &\quad \Omega L_t^{1-\phi} X_t^{\phi} \ , && (1.17)\\
X_t = &\quad \exp \int_0^1 \gamma_j \log X_{jt} dj \ , && (1.18)\\
X_{jt} = &\quad (Z_{jt}^{\frac{\epsilon}{1+\epsilon}} + \sum_k M_{jkt}^{\frac{\epsilon}{1+\epsilon}})^{\frac{1+\epsilon}{\epsilon}} \ , && (1.19)\\
p_t Y_t \geq &\quad w_t L_t + \int_0^1 V_{jt} Z_{jt} dj + \int_J U_{jkt}(1+\tau_{jkt}) M_{jkt} dj \text{ , and} && (1.20)\\
p_t Y_t \leq &\quad \Theta \ . && (1.21)
\end{aligned}
$$

Let the Lagrange multipliers on the budget constraint be Λ_0 and on the enforcement constraint be Λ_1. From the first order condition for labor, the optimal demand for labor input is given as

$$
\begin{aligned}
L_t^* = &\quad (1-\phi)\frac{\widetilde{MC}_t * Y_t^*}{w_t}\left[\frac{1+(\Lambda_0^*-\Lambda_1^*)(1-\beta(1-\gamma))}{1+\Lambda_0^*(1-\beta(1-\gamma))}\right]\\
= &\quad (1-\phi)\frac{\widetilde{MC}_t * Y_t}{w_t}\,\Xi\\
&\text{where} \qquad \Xi = 1-\frac{\Lambda_1^*}{\Lambda_0^*} \ .
\end{aligned}
$$

$\widetilde{MC}_t$ is the marginal cost as defined in equation (1.6). Assume that labor demand is non-negative.

Lemma I.1. $\frac{d\Xi}{d(1+\tau)} < 0$ *that is* $\frac{d\Lambda_0^*}{d(1+\tau)} < 0$ *and* $\frac{d\Lambda_1^*}{d(1+\tau)} > 0$.

Λ_1 is the marginal value of the firm of borrowing. An additional dollar in borrowing would be more valuable to the firm when the expected value of the firm is low. Higher tariffs implies that expected value of the firm is lower. Therefore, output (prices) will be lower (higher). Given a downward sloping demand curve, marginal revenue will be higher.

Proposition 4. The total effects in the presence of the working capital constraint is the sum of the substitution effects, scale effects and working capital effects.

$$\frac{d\log L_t}{d\log(1+\tau_{jkt})} = \underbrace{\frac{d\log \widetilde{MC_t}}{d\log(1+\tau_{jkt})}}_{\text{Substitution Effects}} + \underbrace{\frac{d\log Y_t}{d\log(1+\tau_{jkt})}}_{\text{Scale Effects}} + \underbrace{\frac{d\log \Xi}{d\log(1+\tau_{jkt})}}_{\text{Working Capital Effects}} \tag{1.22}$$

The first and second terms are the substitution effects and scale effects as described in the case without the working capital constraint. With the working capital requirement and some probability that future tariff rate will change, I now have a third term that I will call the *working capital* effects. This term will be non-zero when $\Lambda_1 > 0$, that is, when the enforcement constraint binds. From the enforcement constraint condition, this would only bind if the probability of tariff increasing is non-zero.

Suppose I start from a case whereby the enforcement constraint is not binding and that there is no probability that future tariff rate will rise. If I shut down the financial shock channel, such that θ is equal to one, then the enforcement constraint would only bind when γ increases. In this setup, the total effects of a change in tariff on labor input would be more negative if the firm is also financially constrained.

1.4 Data

Trade transaction data at the firm level for U.S. imports are obtained from the Longitudinal Firm-Level Trade Transactions Data (LFTTD) maintained by the U.S. Census Bureau. This dataset provides transaction level trade information at the firm level for the universe of firms that engage in imports from 1992. As my baseline sample, I first obtained the list of importers in the year 1995. I merged this list of importers to the Longitudinal Business Database (LBD) to obtain the firm's employment information[9]. Next, I merged this list of firms to the LBD for the years 1992 to 1994. For my baseline sample, I kept only the firms that are successfully merged as they would have existed for all these years prior to 1995, to estimate the pre-disruption employment trend. Then, I merged this list of firms over the years from 1996 to 2000. In these later years, I would allow for the deaths of firms. In addition to employment information, the LBD also provides information on the industry, age and multi-unit status of firms. This information is used to generate the covariates used in the fully saturated regression model as described in section 1.5.

The LFTTD dataset also contains information about the preference regime that was applied on each trade transaction. From this information, I calculated the value and share of a firm's imports that entered through the GSP regime. In addition, I also merged additional relevant trade policy indicators such as the list of countries and products that are eligible for GSP and the corresponding tariff rates.

[9]For a given year, the LBD is recorded at the firm-establishment level, while the LFTTD is recorded at the firm level. The merge process is carried out by merging the two datasets using the unique firm identifier that is constructed by the U.S. Census.

This information is obtained from the World Integrated Trade Solution (WITS) website.

The conceptual framework predicts that GSP firms that are more financially constrained are the ones that will be disproportionately impacted by cost-shocks to their input costs. Measures of financial constraints are calculated using firm data from public-listed firms in COMPUSTAT for the years between 1980–2000, based on the methodology pioneered by Rajan and Zingales (1998), and Manova et al. (2014). The first measure is the classic index for external finance dependence, as proxied by the share of capital expenditures not financed from cash flow from operations (CFO). The second measure is the availability of tangible assets to raise external finance, which is proxied as the ratio of *Net Property, Plant and Equipment* to *Total Assets* for each industry. The former measure captures the degree of importance of the initial outlay in firms' financing investment activities, while the latter captures the availability of collateral for firms to raise external finance. Both measures capture two distinct but complementary aspects of how financial constraints could impact firms' activities. To allow for these elements to operate in my estimation, I construct a composite index of financial constraints for each industry, *FC*, by taking the first principal component of these two measures.

1.5 Empirical Approach

The conceptual framework is mapped to the empirical estimation by assigning a binary treatment indicator on firms that have utilized the GSP regime prior to the period of the policy disruption. The primary identification strategy employed in this paper is based on the fully saturated regression model. The estimated regression includes the fully interacted terms of the covariates, which in this case would be observed firm characteristics (size, industry, age and multi-unit status). This approach has been applied in several studies on firms' employment dynamics (Davis et al. (2014), Haltiwanger et al. (2012))[10]. As discussed in Angrist and Pischke (2008), a saturated regression model fits the conditional expectation function (CEF)[11] perfectly and helps to avoid boundary issues related to bounded dependent variables that arise in OLS estimation[12]. The latter point is especially important given that the measure of employment changes that will be employed in this paper is a bounded value, as will be described in the next section.

1.5.1 Baseline Regressions at the Firm Level

The baseline treatment group is defined as importing firms in which GSP imports make up of at least 50 percent of their total imports in the period between 1994 and July 1995. Throughout the paper, this treatment group is referred to as GSP firms. The baseline control group is defined as other importers not included in the treatment group. As we shall see, the intensity of usage of the GSP regime is an important factor that determines the firm's employment outcomes. To verify this point, other measures of usage intensity are calculated as robustness checks. In addition to this binary indicator of treatment and control, as part of the robust-

[10]The advantages of using the fully saturated model are discussed in the web appendix of Haltiwanger et al. (2012).

[11]The conditional expectation function is defined as $\mathbb{E}(y|X)$, with X being the list of covariates.

[12]Theorem 3.1.4 in Angrist and Pischke (2008) states that the CEF is linear when the population regression yields the CEF. This occurs when either the joint normality assumption between y and X holds, or when X is a fully saturated set of dummies.

ness checks, I also calculated a continuous measure of the ratio of the firm's GSP imports relative to its total imports as another measure of the firm's dependence on the GSP regime.

Following Davis et al. (1996), the symmetric growth rate of employment y at establishment e belonging to firm i between periods $t-k$ and t is defined as follows:

$$\Delta y^i_{e,t-k,t} = \frac{y_{e,t} - y_{e,t-k}}{x_{e,t}} \qquad \text{where} \qquad x_{e,t} = 0.5[y_{e,t} + y_{e,t-k}] \ .$$

This measure of symmetric growth rate is bounded between -2 and 2, and thus is convenient as it can accommodate both entry and exit; unlike the case when log differences are used. I aggregated the employment data up to the firm level to provide for consistency in interpretation with the trade transaction information. A fully saturated set of firm level fixed effects is constructed using the four way interactions of firm size bins, age bins, industry and multi-unit status. Industry is defined at the SIC 2 digit level. The categories for firm size are defined in terms of the number of March 12 employment in the following discrete bins: 0–9, 10–25, 26–50, 50–99, 100–249, 250–500, 501–999, 1000–2499, more than 2500. Meanwhile, the categories for firm age is defined in the following bins: 0–2, 3–5, 6–8, 9–11, 12–14, 15–17, 18–20, 21 and above. The definition of a firm's multi-unit status is given in the LBD.

Firms' decisions to import from GSP eligible countries may depend on several factors, including pricing and the availability of alternatives. As long as these factors are orthogonal to firm-level outcomes, this is not a concern. But, if there are omitted factors that drive both a firm's usage of the GSP policy and the firm's outcomes, then the results might be spurious. Therefore, I also included additional controls such as proxy measures for the reliance of a firm on imported products from the GSP regime, measures for quality (proxied by unit values), an indicator for exporters and total value of imports.

The baseline cross-section regression specification is given as follows:

$$\Delta y^i_{t,t+k} = \beta_0 + \beta_1 GSP^i + \mathbf{X'}_t\beta + \nu^i_t + \epsilon^i_t \ , \tag{1.23}$$

where i indexes firms, t indexes years, $\Delta y^i_{t,t+k}$ is the growth rate of employment between year t and year $t+k$, GSP^i is a treatment variable (as defined above) for a firm's utilization of the GSP regime in the pre-treatment period, $\mathbf{X'}_t$ are controls (exporter status, log value of imports, proxy for reliance of top imported products on GSP regime, proxy for quality and price (unit value indicators)) and ν^i_t is the industry s × size z × age a × multi-unit m fixed effects. The variable of interest is β_1, which measures the differential impact on employment for an importer that is affected by the GSP lapses and reinstatements.

Following the conceptual framework, I next examined the role of financial constraints on employment by estimating the following regression:

$$\Delta y^i_{t,t+k} = \beta_0 + \beta_1 GSP^i + \beta_2 GSP^i \times FC_s + \mathbf{X'}_t\beta + \nu^i_t + \epsilon^i_t \ , \tag{1.24}$$

where FC_s is the financial constraint indicator. The framework implies that the coefficient of interest, β_2, will be negative for GSP firms with higher financial constraints.

1.5.2 Additional Specifications

1.5.2.1 Long Difference

The medium-term impact of the GSP shock is estimated by considering a longer time difference of growth rates in employment in the pre-GSP shock period with the period after the large disruption. Following the methodology in Trefler (2004), I define the pre-GSP shock period as 1992–1995 and the post period to be 1995–1998.

$$\Delta y^i_{post} = \left(\frac{y^i_{1998} - y^i_{1995}}{0.5[y^i_{1998} + y^i_{1995}]} \right) /3$$
$$\Delta y^i_{pre} = \left(\frac{y^i_{1995} - y^i_{1992}}{0.5[y^i_{1995} + y^i_{1992}]} \right) /3$$

The baseline specification is given by:

$$\Delta y^i_{post} - \Delta y^i_{pre} = \quad \beta_0 + \beta_1 GSP^i_{1995} + \beta_2 GSP \times FC + \mathbf{X'}_t \beta + \nu^i_t + \epsilon^i_t \,. \qquad (1.25)$$

An alternative specification that includes business conditions control, Δb^i_t, similar to that described in Trefler (2004), was also estimated. Appendix A.3 provides the details on the construction of the business conditions control. The rationale for including the business conditions controls in the context of the GSP shocks is the concern that the industries that are most affected by the GSP shocks could also likely be similarly affected by other macroeconomics shocks. Therefore, I included the measure of business conditions control and re-estimated the following regression:

$$\Delta y^i_{post} - \Delta y^i_{pre} = \quad \beta_0 + \beta_1 GSP^i_{1995} + \beta_2 GSP \times FC + \beta_3(\Delta b^i_{post} - \Delta b^i_{pre}) + \mathbf{X}'_t\beta + \nu^i_t + \epsilon^i_t \; . \tag{1.26}$$

1.5.2.2 Extensive Margin

In addition to estimating the intensive margin effects of the GSP shock, I next consider how the GSP shock could impact the likelihood for a firm to die; i.e. the extensive margin effects[13]. To examine this effect, I used the semi-parametric Cox regression model (Cox, 1972) that is based on survival analysis. The model defines the hazard rate for a firm to be a function of firm-specific factors. My baseline model is given as follows:

$$h_i(t|.) = h_0(t)\exp(\alpha_0 + \alpha_1 GSP_i + \mathbf{X_i'}\alpha_{\mathbf{X}} + \epsilon_t) \; ,$$

where $h_i(t|.)$ is the hazard rate or risk of failure of incumbent firm i at time t, conditional on a set of regressors. This model consists of two components. First, $h_0(t)$ is the unspecified baseline hazard function which depends only on t and not on i. The second component consists of an expression for the covariates $\exp(\alpha_0 + \alpha_1 GSP_i + \mathbf{X_i'}\alpha + \epsilon_t)$. The ratio of firm i's hazard is proportional to another firm j's

[13] Since I have restricted the sample of firms to consider the impact of the GSP shock on firms that imported in year 1995, by construction, the sample does not include any firm birth in subsequent years.

hazard:

$$\begin{aligned}\frac{h(t|x_i)}{h(t|x_j)} =& \frac{\exp(\alpha_0 + \alpha_1 GSP_i + \mathbf{X_i'}\alpha_{\mathbf{X}} + \epsilon_t)}{\exp(\alpha_0 + \alpha_1 GSP_j + \mathbf{X_j'}\alpha_{\mathbf{X}} + \epsilon_t)} \\ =& \exp(\alpha_1(GSP_i - GSP_j) + (\mathbf{X_i'} - \mathbf{X_j'})\alpha_{\mathbf{X}})\end{aligned} \tag{1.27}$$

As shown in equation (1.27), this model can only identify relative hazard between firms, and not the absolute hazard rate since $h_0(t)$ drops out. In this framework, α_1 is the variable of interest. The remaining control variables are similar to the ones used in the employment changes regressions. The coefficients α's in the hazard model are estimated using the maximum likelihood method.

To map the survival model more closely to the intuition of the theoretical framework, I introduced an interaction term between the *GSP* indicator with the financial constraint measure.

$$h_i(t|.) = h_0(t)\exp(\alpha_0 + \alpha_1 GSP_i + \alpha_2 FC_i + \alpha_3 GSP_i \times FC_i + \mathbf{X_i'}\alpha_{\mathbf{X}} + \epsilon_t) \tag{1.28}$$

1.5.2.3 Decomposition into Establishment Births, Acquisitions, Continuers, Deaths and Divestitures

I further decomposed the effects of the GSP shock for each firm into its separate components to understand the margin that has driven the changes in firms' net job creation. As discussed in Haltiwanger et al. (2012), changes in gross job creation and destruction could reveal interesting dynamics that could otherwise be missed in simply looking at only net job creation. A detailed description of the methodology is provided in Appendix A.3.

A firm in the LBD could either be a single-unit firm or a multi-unit firm. For multi-unit firms, their establishments can be defined as births, continuers, acquisitions, divestitures and deaths. A *birth* is assigned when the establishment makes its first appearance in the LBD, while a *death* is assigned when the establishment ceases to exist in the year. Establishments that exist for two consecutive years are deemed to be *continuers*. An existing establishment that switches ownership (*FIRMID*) is defined as an *acquisition* for the new firm and a *divestiture* for the old firm. This decomposition can be expressed in the following way:

$$\Delta y^{i}_{t,t+k} = jc^{continuer}_{t+k} + jc^{birth}_{t+k} + jc^{acquisition}_{t+k} - jd^{death}_{t+k} - jd^{divestiture}_{t+k} - jd^{continuer}_{t+k} \;, \tag{1.29}$$

where jc^{m}_{t+k} is the job creation rate at establishments of type m, with $m \in$ (continuer, birth, acquisition), while jd^{m}_{t+k} is the job creation rate at establishments of type m, with $m \in$ (continuer, death, divestiture).

1.6 Results

The baseline results estimated based on equations (1.23) and (1.24) show that GSP firms registered lower employment growth rates relative to controls in the years after the large disruption in the GSP policy. Specifically, Table 1.2 shows the employment changes for firms for the years 1996–2000, relative to the base year of 1995. In the first year after the first major GSP policy shock, the growth rate of employment of a GSP firm is 3.33 percentage points lower than the control. The difference in growth rates remains significant in the range of between 3.4 and 3.95 percentage points up until the year 1999.

Table 1.3 presents the results with both the level effects of the GSP shock and the estimate of the interaction term between the *GSP* indicator and the measure of financial constraint (*FC*). The results show that firms that are in industries that are more financially constrained, and thus are likely to be more susceptible to binding working capital constraints arising from the periods of lapses and reinstatements of the policy regime, experienced significantly lower employment growth rates in the first three years after the large policy disruption in 1995. The marginal impact of a one percent increase in the measure of external finance dependence is a difference in employment growth rate by about 2 to 4 percentage points in the three years after the shock. The impact is estimated to last for three years as the difference between the GSP firms and the control dissipated after that.

Using a longer time horizon in measuring growth rates, the difference in growth rates in the post-shock period relative to the pre-shock period is shown in Table 1.4. The results are found through a comparison between the three-year difference in the growth rates of employment during the period before and after the policy shock as estimated from equations (1.25) and (1.26). Columns (1) and (2) present the results for (1.25), with the former showing the results without additional controls and the latter with the additional controls. The signs of the coefficients are similar in both regressions. Using column (2) as my preferred regression, the total annualized employment growth rate for GSP firms with a one percent higher measure of financial constraint in the period after the policy disruption is about 4.1 percentage points lower than non-GSP firms.

With the inclusion of the business conditions control, I find that both the sign and the magnitude of the coefficients of interest (on the *GSP* indicator and on the interaction of the *GSP* indicator with *FC*) are similar to that estimated in columns (1) and (2). With column (4) as my preferred regression, I find that the marginal effect of a one percent higher measure of financial constraint corresponds to a 1 percentage point lower employment growth rate.

Given that the magnitude of the differences in growth rates between GSP firms and controls is quite large, one hypothesis could be that the difference is driven by the death of firms. As such, the hazard models as described in equations (1.27) and (1.28) are estimated. Table 1.5 reports the results of the proportional changes for the hazard ratio, i.e. the odds ratio. Coefficients larger than one signify an increased risk of failure, while values less than one signify decreased risk. Columns (1) and (2) present the results from equation (1.27) and I find that the GSP firms have between 6.3 and 7.1 percent higher hazard rate than non-GSP firms. Furthermore, the coefficient on the interaction term between *GSP* and *FC* is negative and significant, implying that financial constraints have been the additional margin that contributed towards slower employment growth for GSP firms.

So far, the results show that the GSP firms have indeed experienced slower employment growth rates following the policy disruption. To understand the margin that contributes towards this differences in growth rates, I decomposed the firm level measure of net job flows as given by equation (1.29). Across the years after the policy disruption, the results presented in Figure 1.1 show that job destruction at continuing establishments provides the largest contributions towards the differences in net job flows between GSP and non-GSP firms.

1.6.1 Counterfactual Exercise

The counterfactual exercise in this section seeks to estimate the effect of being reliant on the GSP policy on employment in the sample. The main assumption for this exercise is that it is partial equilibrium in nature, such that aggregate prices and wages are held constant. As discussed in the introduction, this assumption is appropriate in this study, since only a subset of importers are directly affected by the GSP policy shocks.

The first step to calculate the counterfactual losses in employment due to the GSP shock is to define T as the mapping from symmetric growth rates to the end-period level, holding the initial level fixed (Chodorow-Reich, 2014).

$$\Delta y_{i,t-k,t} = \frac{T[\Delta y_{i,t-k,t}] - y_{i,t-k}}{0.5[T[\Delta y_{i,t-k,t}] + y_{i,t-k}]} \qquad \text{and so,} \qquad T(x) = \frac{1+0.5x}{1-0.5x} y_{i,t-k} \ .$$

Let the counterfactual employment growth rate of a GSP firm i be given by:

$$\Delta y^{cf}_{i,t-k,t} = \mathbf{E}[\Delta y_{i,t-k,t} | GSP = 0]$$

and the fitted employment growth rate of firm i as:

$$\Delta \hat{y}_{i,t-k,t} = \mathbf{E}[\Delta y_{i,t-k,t} | GSP = 1] \ .$$

Using the above mapping, let's define the counterfactual period t employment level for GSP firms as

$$y_{i,t}^{cf} = T[\Delta y_{i,t-k,t}^{cf}]$$

and the fitted value employment level as

$$\hat{y}_{i,t} = T[\Delta \hat{y}_{i,t-k,t}] \ .$$

The total sample employment losses due to the GSP shock would be

$$\sum_{i,GSP_{base}=1} [y_{i,t}^{cf} - \hat{y_{i,t}}] \ .$$

The proportion of net employment change in the sample of GSP firms due to the policy shock is calculated as

$$\frac{\sum_{i,GSP=1}[y_{i,t}^{cf} - \hat{y_{i,t}}]}{\sum_{i,GSP=1}[y_{i,t-k} - y_{i,t}]} \ .$$

Table 1.1: Counterfactual calculations of the effects of GSP on firms in the sample

	1995–1998
Employment decline relative to 1995	−5.4%
Share of losses due to GSP	61%

Table 1.1 shows the results from this exercise. Total employment at GSP firms in the sample declined by 5.4 percent in 1998 compared to 1995. Over the next

three-year period after the shock, the counterfactual employment growth rate from shutting down the GSP shock for this firm could mitigate about 60 percent of these losses.

1.6.2 Robustness Checks

This section provides the results from various robustness checks. First, I consider an alternative time period to investigate if the pattern of lower employment growth rates experienced by GSP firms is simply a characteristic of this type of firm or if, indeed, the GSP policy shock is an important feature that caused the differences in growth rates. Second, I consider alternative measures of GSP usage intensity. Firms that are more dependent on the GSP regime would likely be more vulnerable to the policy shock. Third, I consider an alternative regression specification by estimating a panel regression model with firm fixed effects. This specification estimates the within-firm changes in employment outcomes and absorbs the (constant) unobserved firm-specific characteristics. This specification would, to some degree, test the plausibility of the assumption of no selection on unobservables into utilization of the GSP regime that is made in the saturated regression model.

1.6.2.1 Placebo time sample

The period of annual lapses and reinstatements of the GSP policy abated at the end of 2001. After September 11, 2001, the U.S. Congress authorized a longer period of renewal of five years, from end-2001 until 2006. Absent of such policy lapses and reinstatements, the impact of the GSP shocks on firms' employment should not be evident during this period. To verify this fact, I repeated the firm-level analysis by estimating equations (1.23) and (1.24) on the sample for the period 2002–2006.

The results from this placebo time sample are presented in Tables 1.7 and 1.8. In both tables, the coefficient on the *GSP* indicator is shown to be not significantly different from zero at the 5 percent level. Moreover, the coefficients on the interaction term between the *GSP* indicator and the financial constraint indicator are positive and significant for all years during this period. The results from both tables support the hypothesis that the GSP firms are not shedding employment at a higher pace relative to controls during the period in which the policy is more stable.

1.6.2.2 Other measures of GSP usage intensity

I reestimated the baseline regressions using two different definitions of a GSP firm. One would expect that the impact of the GSP policy shock be greater for firms with higher intensity of usage. The first alternative defines the GSP firm as one with 75 percent of its imports sourced using the regime. Table 1.9 and Table 1.10 present the results for this definition of a GSP firm. In Table 1.9, I find that the growth rate of the GSP firm, measured this way, is 3.3 percentage points lower relative to controls in 1996. For the next three years, the estimated growth rates widened further and remained negative and significant at 5.4 percentage points lower than controls in 1999. In Table 1.10, the coefficient on the *GSP* indicator follows a similar pattern as described in Table 1.9. The coefficient on the interaction term between the *GSP* indicator and *FC* is negative and significant in 1997 and 1998. The magnitude of the marginal effects of the GSP policy shock for firms that are more financially constrained is larger for GSP firms under this definition than what was found in the baseline result.

The second measure defines the GSP firm as one with any percentage of its imports being sourced using the regime. The results are presented in Table 1.11 and Table 1.12. With this definition of a GSP firm, I find that the impact of the policy shock is not significantly different to the growth rates of the controls. Putting these results together, it suggests that there is a monotonic relationship between the degree in which a firm utilizes the GSP regime and the effects on its employment outcomes. A greater dependence on the GSP regime, measured as a percentage of GSP imports, is associated with larger negative employment effects.

Similar outcomes are also obtained using the long difference of employment changes as the dependent variable. In Table 1.13, Panel A and B show the results with *GSP* at 75 percent and any intensity respectively. Comparing the preferred specifications in columns (4) and (8), I find that GSP firms defined with a 75 percent intensity experienced a larger change in the decline in employment growth rates (3 percentage points) after the policy disruption relative to controls. This estimate is larger than the baseline estimate of 2.7 percentage points as shown in Table 1.4. The marginal effect of a one percent increase in the measure of the financial constraint index on GSP firms in the case of the 75 percent intensity is broadly similar in magnitude with the baseline (1.11 percentage points compared to 1.07 percentages points). However, for the case in which the GSP firms are defined to be firms that imported using the GSP regime, regardless of intensity of use, the marginal effect of a one percent increase in the measure of the financial constraint index is insignificant.

1.6.2.3 Controlling for Firm Fixed Effects

The baseline regression was estimated by comparing GSP firms with a set of controls defined within particular cells (defined as the interaction of industry, age, multi-unit status and size). Nonetheless, one way that these results could be confounded would be due to the prevalence of unobserved firm specific characteristics. In this set of robustness checks, the regressions are specified with firm fixed effects to absorb these firm-level characteristics. Since both the *GSP* and *FC* indicators are not time-varying, the level coefficients on these indicators are not identified. Therefore, to identify the marginal effects of the GSP shocks on firms' employment outcomes, the interaction term between *GSP*, *FC* and the time indicator, *POST*, is examined. *POST* is a binary indicator; defined as unity for the years in which the GSP policy was more disruptive (1996–1998) and 0, otherwise. Year fixed effects are also included to control for any time trends in the growth rates in employment. The dependent variable is the annual change in firm employment. I estimated the following firm-level equation:

$$\begin{aligned}\Delta y^i_{t,t+1} = \quad & \beta_0 + \beta_1 POST_t \times GSP^i \times FC^i + \beta_2 POST_t \times GSP^i + \\ & \beta_3 POST_t \times FC^i + \eta^i + \mu_t + \epsilon^i_t \ , \end{aligned} \tag{1.30}$$

where η^i is the firm fixed effect and μ_t is the year fixed effect. The coefficient of interest is β_1 in that it measures the marginal effects of the policy disruption on GSP firms that are more financially constrained.

Column (1) in Table 1.6 shows the results for the whole sample. Overall, GSP firms that are more financially constrained registered lower annual growth rates in employment (the marginal effect from policy shock and financial constraint is -2.3 percentage points) during the years after the policy disruption. One could also be interested to examine the differences in effects for single-unit firms vis-à-vis multi-unit firms. By comparing the regression coefficients in columns (2) and (3), I find that the negative marginal employment growth effect is significant only for single-unit firms (-2.7 percentage points). Meanwhile, the marginal effect of the GSP shocks on multi-unit firms is not significant. This result provides some suggestive evidence that single-unit firms (typically smaller) are more vulnerable to policy disruptions.

1.7 Conclusion

In this paper, I show that the effect of uncertain policy disruptions on firms' employment outcomes is both significant and economically important. Using the GSP policy disruption in 1995–1996 as an event study, firms that were affected by the GSP policy disruption experienced between 3 to 4 percentage points lower employment growth in the four years after the disruption.

These results provide evidence that support the popular conjecture that policy uncertainty does indeed impact real economic activity negatively. One important policy implications from the results is that policy uncertainty arising from the lapses and reinstatements of public policies could inadvertently lead to the opposite outcome from the original intent of the policy. Policies that are intended to boost employment or investment could, in practice, do just the opposite.

Although this paper does not explicitly study the utilization of the GSP regime, some related studies (see Jones (2015)) have found that GSP utilization is low and has declined over time[14]. Policy uncertainty of this regime could potentially further reduce the utilization rate since it creates an additional cost for firms to utilize the regime. This explanation suggests an additional channel in which policy uncertainty could fail to achieve its intended outcome by raising the implicit fixed cost of entry.

The findings of this paper suggest that the impact of policy uncertainties on firm outcomes is likely to be quite important in most settings. Future work could consider extensions towards understanding of policy uncertainties on other firm choices (such as mark-ups, buyer-seller margins and sourcing patterns).

[14]Reasons that have been studied include insufficient preference margins given the fixed costs of preference utilization, information asymmetry, lack of infrastructure, etc.

Table 1.2: Growth Rates of Firm's Employment Relative to 1995

	Growth Rates of Firm's Employment Relative to 1995						
	1993	1994	1996	1997	1998	1999	2000
GSP (50 percent)	−0.0257***	−0.0041	−0.0333**	−0.0192	−0.0395**	−0.0341*	−0.0289
	[0.0098]	[0.00822]	[0.0143]	[0.0170]	[0.0190]	[0.0195]	[0.0216]
R-squared	0.145	0.105	0.08	0.072	0.074	0.075	0.076
No of Firms	76000	76000	76000	76000	76000	76000	76000
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes

[a] Fixed Effects (FE) are the interactions of Age X Size X Multi-Unit X Industry.
[b] Standard errors are clustered at the Age X Size X Multi-Unit X Industry level.

Table 1.3: Growth Rates of Firm's Employment Relative to 1995 (With Financial Constraint Index)

	Growth Rate of Firm's Employment Relative to 1995						
	1993	1994	1996	1997	1998	1999	2000
GSP (50 percent)	−0.0257***	−0.0041	−0.0332**	−0.0190	−0.0394**	−0.0340*	−0.0288
	[0.00983]	[0.00820]	[0.0141]	[0.0168]	[0.0190]	[0.0194]	[0.0216]
GSP $\times$ FC	−0.0043	0.0016	−0.0206*	−0.0401**	−0.0343*	−0.0237	−0.0079
	[0.00980]	[0.00760]	[0.0121]	[0.0160]	[0.0187]	[0.0181]	[0.0195]
R-squared	0.145	0.105	0.08	0.072	0.074	0.075	0.076
No of Firms	76000	76000	76000	76000	76000	76000	76000
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

[a] Fixed Effects (FE) are the interactions of Age X Size X Multi-Unit X Industry.
[b] Standard errors are clustered at the Age X Size X Multi-Unit X Industry level.
[c] FC is the measure of external finance dependence calculated using the principal component method.

Table 1.4: Long Difference in Growth Rates of Employment

	Long Difference in Growth Rates of Employment			
	(1)	(2)	(3)	(4)
GSP (50 percent)	−0.0103	−0.0272***	−0.0092	−0.0270***
	[0.007]	[0.0075]	[0.007]	[0.007]
GSP $\times$ FC	−0.0152*	−0.0145*	−0.0108*	−0.0107*
	[0.009]	[0.009]	[0.006]	[0.0056]
$\Delta b^i_{post} - \Delta b^i_{pre}$			0.644***	0.211
			[0.185]	[0.193]
Observations	76000	76000	76000	76000
R-squared	0.146	0.151	0.093	0.099
Other Controls	No	Yes	No	Yes
Clustered S.E.	Yes	Yes	Yes	Yes

[a] Fixed Effects (FE) for Columns (1) and (2) are the interaction term of Age X Size X Multi-Unit Status. For Columns (3) and (4), the fixed effects are Age X Size X Multi-Unit X Industry.
[b] Standard errors are clustered at the Age X Size X Multi-Unit X Industry level.
[c] FC is the measure of external finance dependence calculated using the principal component method.

Table 1.5: Proportional Cox Model

	Odds Ratio (1)	Odds Ratio (2)	Odds Ratio (3)	Odds Ratio (4)
GSP (50 percent)	1.063*	1.071**	1.062*	1.071**
	[0.0344]	[0.0375]	[0.0338]	[0.0370]
FC			0.9910	0.9330
			[0.0151]	[0.0531]
GSP × FC			1.067*	1.060*
			[0.0413]	[0.0373]
Observations	76000	76000	76000	76000
Sample	All Importers	All Importers	All Importers	All Importers
Other Controls	No	Yes	No	Yes

[a] FC is the measure of external finance dependence calculated using the principal component method.

Table 1.6: Annual Growth Rates of Employment with Firm Fixed Effects

	Annual growth rates of employment		
	All Importers	Single-Unit	Multi-Unit
	(1)	(2)	(3)
GSP (50 percent) × FC × POST	−0.0229***	−0.0266***	−0.0182
	[0.00816]	[0.00879]	[0.0217]
GSP (50 percent) × POST	−0.0182*	−0.0236**	0.0236
	[0.00958]	[0.0107]	[0.0213]
FC × POST	0.00522***	0.00871***	0.0027
	[0.00196]	[0.0029]	[0.0024]
No of Firms	76000	59000	18000
R-squared	0.231	0.226	0.262
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes

[a] *POST* is an indicator variable (1 for years 1996, 1997, 1998; and 0 for years 1993, 1994, 1995).
[b] Standard errors are clustered at firm level.
[c] FC is the measure of external finance dependence calculated using the principal component method.

Table 1.7: Alternative Time Period

	Growth Rates of Firm's Employment Relative to 2002				
	2001	2003	2004	2005	2006
GSP (50 percent)	−0.0155	−0.0243*	−0.023	−0.0283	−0.0177
	[0.00988]	[0.0131]	[0.0179]	[0.0188]	[0.0205]
R-squared	0.097	0.051	0.058	0.064	0.071
No of Firms	98000	98000	98000	98000	98000
Other Controls	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes	Yes

[a] Fixed Effects (FE) are the interactions of Age X Size X Multi-Unit X Industry.
[b] Standard errors are clustered at the Age X Size X Multi-Unit X Industry level.

Table 1.8: Alternative Time Period (With Financial Constraint Index)

	Growth Rates of Firm's Employment Relative to 2002				
	2001	2003	2004	2005	2006
GSP (50 percent)	−0.0163	−0.0256*	−0.0245	−0.0306	−0.0201
	[0.00991]	[0.0132]	[0.0179]	[0.0189]	[0.0205]
GSP × FC	0.0176*	0.0275**	0.0315**	0.0488***	0.0517***
	[0.00942]	[0.0123]	[0.0153]	[0.0183]	[0.0198]
R-squared	0.097	0.051	0.058	0.064	0.071
No of Firms	98000	98000	98000	98000	98000
Other Controls	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes	Yes

[a] Fixed Effects (FE) are the interactions of Age X Size X Multi-Unit X Industry.
[b] Standard errors are clustered at the Age X Size X Multi-Unit X Industry level.

Figure 1.1: Decomposition of the Contribution of Net Job Flows into Components

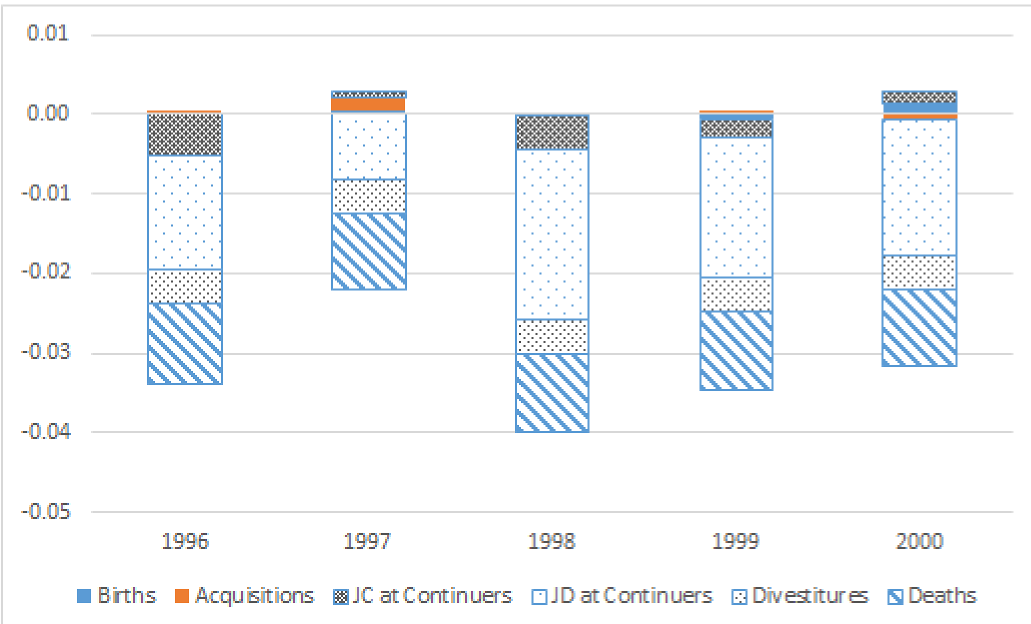


Table 1.9: Alternative Measures of Intensity of GSP Usage - 75 percent

	Growth Rates of Firm's Employment Relative to 1995						
	1993	1994	1996	1997	1998	1999	2000
GSP (75 percent)	−0.0169	−0.0040	−0.0331**	−0.0427**	−0.0654***	−0.0543***	-0.0360
	[0.0114]	[0.00916]	[0.0149]	[0.0191]	[0.0207]	[0.0205]	[0.0234]
R-squared	0.145	0.105	0.08	0.072	0.074	0.075	0.076
No of Firms	76000	76000	76000	76000	76000	76000	76000
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes

[a] Fixed Effects (FE) are the interactions of Age X Size X Multi-Unit X Industry.
[b] Standard errors are clustered at the Age X Size X Multi-Unit X Industry level.

Table 1.10: Alternative Measures of Intensity of GSP Usage - 75 percent (with Financial Constraint Index)

	Growth Rate of Employment Between Year and 1995 (DHS)						
	1993	1994	1996	1997	1998	1999	2000
GSP (75 percent)	−0.0168	−0.0040	−0.0328**	−0.0417**	−0.0643***	−0.0535***	−0.0354
	[0.0114]	[0.009]	[0.0148]	[0.0189]	[0.0205]	[0.0203]	[0.0233]
GSP $\times$ FC	−0.0039	0.0003	−0.0123	−0.0410**	−0.0423**	−0.0303	−0.0226
	[0.0102]	[0.008]	[0.0121]	[0.0178]	[0.0204]	[0.0197]	[0.0216]
R-squared	0.145	0.105	0.08	0.072	0.074	0.075	0.076
No of Firms	76000	76000	76000	76000	76000	76000	76000
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes

[a] Fixed Effects (FE) are the interactions of Age X Size X Multi-Unit X Industry.
[b] Standard errors are clustered at the Age X Size X Multi-Unit X Industry level.
[c] FC is the measure of external finance dependence calculated using the principal component method.

Table 1.11: Alternative Measures of Intensity of GSP Usage - Any Percent

	Growth Rates of Firm's Employment Relative to 1995						
	1993	1994	1996	1997	1998	1999	2000
GSP (Any percent)	−0.0545***	−0.0604***	−0.0253	−0.0078	−0.0023	0.0001	0.0144
	[0.0161]	[0.0138]	[0.0164]	[0.0204]	[0.0246]	[0.0263]	[0.0271]
R-squared	0.145	0.105	0.08	0.072	0.074	0.075	0.076
No of Firms	76000	76000	76000	76000	76000	76000	76000
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes

[a] Fixed Effects (FE) are the interactions of Age X Size X Multi-Unit X Industry.
[b] Standard errors are clustered at the Age X Size X Multi-Unit X Industry level.

Table 1.12: Alternative Measures of Intensity of GSP Usage - Any Percent (with Financial Constraint Index)

	Growth Rate of Employment Between Year and 1995 (DHS)						
	1993	1994	1996	1997	1998	1999	2000
GSP (Any percent)	−0.0545***	−0.0604***	−0.0252	−0.0078	−0.0023	0.0001	0.0144
	[0.0161]	[0.0138]	[0.0164]	[0.0204]	[0.0246]	[0.0263]	[0.0271]
GSP $\times$ FC	−0.0002	0.0011	−0.0027	−0.0048	−0.0034	0.0007	0.0037
	[0.00586]	[0.00397]	[0.00543]	[0.00825]	[0.0132]	[0.0120]	[0.0113]
R-squared	0.145	0.105	0.08	0.072	0.074	0.075	0.076
No of Firms	76000	76000	76000	76000	76000	76000	76000
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes

[a] Fixed Effects (FE) are the interactions of Age X Size X Multi-Unit X Industry.
[b] Standard errors are clustered at the Age X Size X Multi-Unit X Industry level.
[c] FC is the measure of external finance dependence calculated using the principal component method.

Table 1.13: Long Difference in Growth Rates of Employment (Other Measures of GSP Usage Intensity)

	Long Difference in Growth Rates of Employment			
	(1)	(2)	(3)	(4)
Panel A: Indicator Variable is GSP user (75 percent)				
GSP (75 percent)	-0.0181**	-0.0326***	-0.0147*	-0.0303***
	[0.0082]	[0.0086]	[0.00800]	[0.0086]
GSP $\times$ FC	-0.0158*	-0.0164*	-0.0107*	-0.0111*
	[0.0092]	[0.009]	[0.00575]	[0.0057]
$\Delta b^i_{post} - \Delta b^i_{pre}$			0.643***	0.21
			[0.185]	[0.193]
Observations	76000	76000	76000	76000
R-squared	0.146	0.151	0.093	0.099
Other Controls	No	Yes	No	Yes
Clustered SE	Yes	Yes	Yes	Yes

	Long Difference in Growth Rates of Employment			
	(5)	(6)	(7)	(8)
Panel B: Indicator Variable is GSP user (any)				
GSP (Any percent)	0.0107***	-0.0234**	0.00752**	-0.0252**
	[0.0037]	[0.00996]	[0.0037]	[0.0099]
GSP $\times$ FC	-0.004	-0.003	-0.002	-0.002
	[0.0046]	[0.0042]	[0.0029]	[0.0028]
$\Delta b^i_{post} - \Delta b^i_{pre}$			0.649***	0.213
			[0.186]	[0.193]
Observations	76000	76000	76000	76000
R-squared	0.146	0.151	0.093	0.099
Other Controls	No	Yes	No	Yes
Clustered SE	Yes	Yes	Yes	Yes

[a] Fixed Effects (FE) for Columns (1), (2), (5) and (6) are the interaction term of Age X Size X Multi-Unit Status. For Columns (3), (4), (7) and (8) the fixed effects are Age X Size X Multi-Unit X Industry.
[b] Standard errors are clustered at the Age X Size X Multi-Unit X Industry level.
[c] FC is the measure of external finance dependence calculated using the principal component method.

CHAPTER II

Measuring Misallocation in U.S. Manufacturing (with Dimitrije Ruzic)[1]

2.1 Introduction

Misallocation can only be measured against a clearly specified alternative: how would resources be allocated in the absence of distortions? Building on the ideas of Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), a large literature infers misallocation as the improvement in aggregate productivity from equalizing marginal revenue products across establishments. We highlight a key identification issue in this literature: a standard implementation cannot separately identify the production function parameters and the distortions faced by establishments. This lack of identification can induce spurious correlations between productivity and distortions, leading the econometrician to mismeasure misallocation. We first show

[1]DISCLAIMER: "Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed."

how misallocation measures in this class of models can be identified even when we cannot identify all the model parameters. We then formally derive the biases associated with mismeasuring production-function parameters and quantify them using U.S. Census microdata.

To illustrate the close link between production-function parameters and measures of misallocation, we turn to a standard example used in this literature. Consider two equally-productive establishments. If one establishment faces barriers to acquiring capital, it uses less capital and has a higher marginal product of capital. If we could reallocate inputs across the two establishments so as to equalize their marginal products, this economy would produce more output and have higher measured productivity. In this example both establishments are equally productive; productivity and distortions are uncorrelated. We emphasize that mismeasuring production-function parameters induces spurious correlations between productivity and distortions where none may exist.

Consider a setting in which Cobb-Douglas production technology combines capital and labor. If the econometrician overstates the output elasticity of labor, she perceives as more productive the establishments that employ relatively more capital than labor. Returning to the earlier example, the establishment with the capital distortion uses less capital and its inferred productivity would be lower. Conversely, by overstating the output elasticity of capital, the econometrician perceives as more productive the establishments that employ relatively less capital than labor. In the example, the establishment facing the distortion now has a higher inferred productivity than its counterpart. In both cases, mismeasurement of the production-function elasticities induces spurious correlations between productivity and distortions.

These spurious correlations are impediments to measuring misallocation correctly. In a hypothetical exercise where distortions are equalized across establishments, there are two reasons the econometrician might expect aggregate productivity to improve. First, equalizing distortions across equally-productive establishments reallocates inputs in a manner that equalizes marginal products. This re-allocation transfers inputs from where the marginal products are low to where they are high, and, in the process, increases output. Second, if the most productive firms face the largest distortions, then this counterfactual would disproportionaly unburden the most productive firms and lead to even larger aggregate productivity gains. If there is no correlation between productivity and distortion, as in the example above, then this second channel is muted. If the econometrician induces a spurious positive correlation between the two, then the second channel is operational. However, the aggregate productivity improvement from the second channel is fictitious: true productivity is uncorrelated with distortions and this increase in aggregate productivity cannot be realized. In this manner, the econometrician could overstate misallocation.

We emphasize these particular biases because production-function parameters in models of misallocation are generally not identified. For instance, in the original Hsieh and Klenow (2009) implementation, the authors use three observations for each establishment in an industry: value added, expenditures on labor, and perpetual-inventory measures of the capital stock. To measure misallocation, the authors then back out three parameters for each establishment: a measure of TFP, and two distortions, one for each first-order condition. In addition to these establishment-level parameters, the measurement of misallocation requires a production-function parameter that is common to all establishments in the industry: an output elasticity of labor in a constant-returns-to-scale production function. If there are N establishments in an industry, there are $3N$ data points with which to identify $3N + 1$ parameters. Indeed, Hsieh and Klenow (2009) state that they "cannot separately identify the average capital distortion and the... production elasticity in each industry." If this lack of identification leads to incorrectly estimated production-function parameters, then the econometrician will mismeasure establishment-level productivity and aggregate misallocation.

We resolve this identification problem in two steps. First, we show that the measure of misallocation requires knowledge of relative distortions within an industry. In the process, we eliminate the level of the average distortions from the parameter space for measuring misallocation. Second, we highlight the fact that the model is agnostic about the mapping of the distortions to the data; these distorts are wedges in establishment first-order conditions. There are multiple model-consistent ways of specifying where in the establishment profit function the distortions are located. Given the data available in the U.S. Census of Manufactures, we cannot identify production function parameters with a commonly-used profit function where distortions fall on firm size and the capital-labor ratio. However, we can identify the production function parameters with a profit function where the distortions fall directly on the labor and capital input choices. Together, these two steps allow us to measure misallocation in a model-consistent manner.

Our emphasis on production-function-driven biases is also a means of bridging the literatures on misallocation and on returns to scale (RTS). The large literature building on the work of Hsieh and Klenow (2009) tends to assume constant-returns-to-scale production technologies with labor elasticities that vary across industries. A separate literature, including Hall (1990), Basu and Fernald (1997), and Basu et al. (2006), has suggested that the returns to scale in production plausibly differ across industries. Consequently, incorrectly imposing constant RTS can lead to the types of biases we detail in this paper.

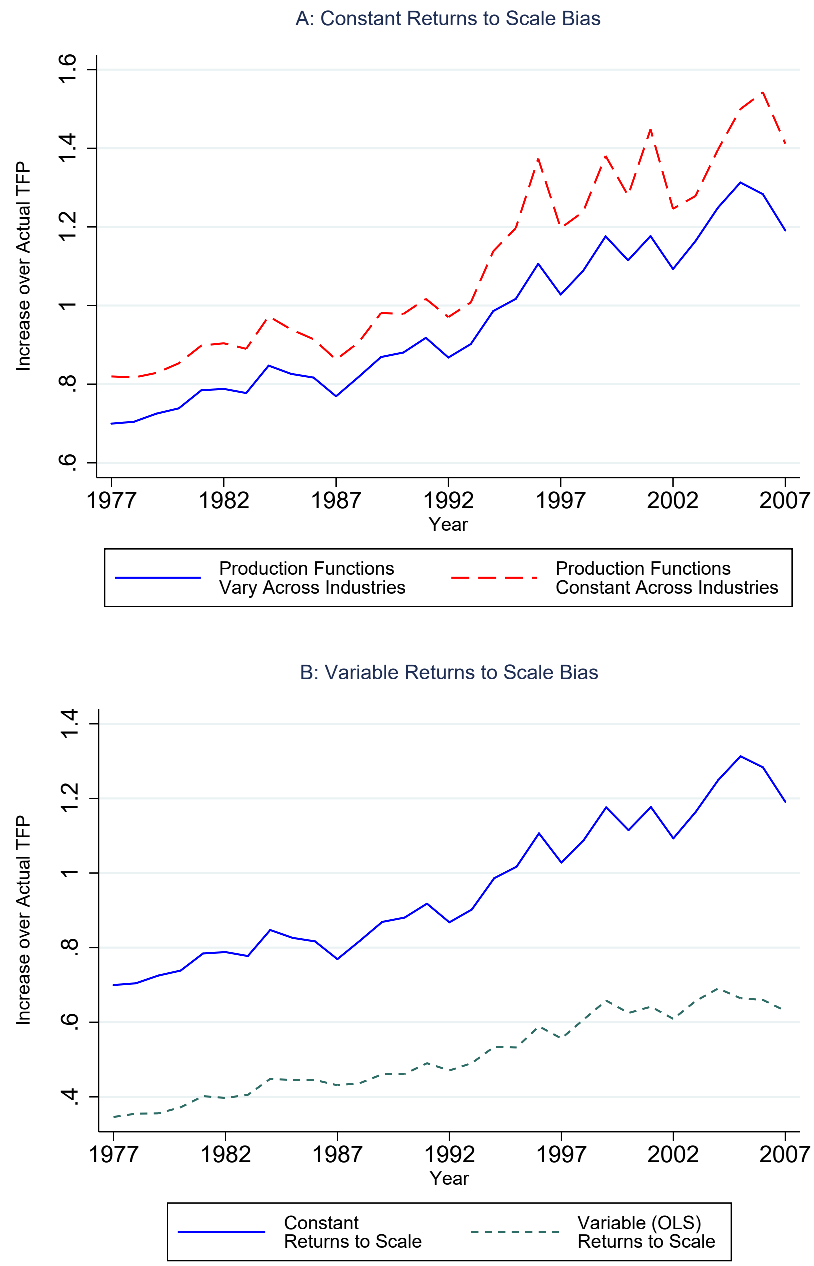
Figure 2.1 presents two cases of mismeasurement for U.S. manufacturing misallocation. In each panel, the vertical axis measures the increase over U.S. manufacturing TFP from equalizing distortions across establishments in an industry. The horizontal axis is time in years. In both panels, the solid blue line plots measured misallocation for the identified constant returns-to-scale model. For this model, production-function parameters vary by industry. In panel A, we compare this identified model to one where we instead identify a single, constant RTS production function across all industries (dashed red line). In this comparison, misallocation in U.S. manufacturing is overstated by 10–25%, depending on the year. Underlying this positive aggregate bias is a collection of industries, some of which see their labor output elasticities overstated and some see it understated. In section 2.3 we derive the expressions showing that the direction of the industry-level bias depends on the direction in which the labor elasticity is mismeasured, as well as the underlying correlation of productivity and capital-labor ratios in the industry. In section 2.6 we corroborate these predictions at the industry level and then show how the different industry biases aggregate to produce the aggregate bias.

In panel B, we compare the identified constant RTS model to one in which we allow returns to scale in production to be variable. Our currently disclosed measures suggest that most industries face decreasing returns to scale in production at the establishment level. Consistent with the bias expressions we derive, overstating RTS by assuming RTS are constant leads to an overstatement of measured misallocation. The green dashed line in panel B reflects the smaller estimates of manufacturing misallocation when returns to scale are allowed to vary.[2]

We see this paper contributing most directly to the misallocation literature by identifying the parameters for measuring misallocation in this commonly-used framework. Beyond these direct contributions, we hope that our characterization of production-function-driven biases highlights the importance of identifying model-consistent production functions. In a variety of economic settings, an alternative characterization of the world might require reestimation of production functions. Consider, for instance, models in which firms pay fixed costs in terms of labor, perhaps to access a market. Faced with data on value added and labor expenditures, the econometrician might be tempted to infer a labor output elasticity as the ratio of labor expenditures to value added. However, if firms pay fixed

[2]Our currently disclosed estimates of RTS comprise the same identified labor elasticity as in the constant RTS model and a capital elasticity that is estimated using OLS. We think the current estimates likely overstate the extent of decreasing returns to scale and hence **overstate** the measurement bias from allowing for non-constant returns to scale. We are working on a model-consistent way to estimate the capital elasticity accounting for unobserved productivity differences across establishments using a dynamic panel procedure detailed later in the paper. We plan to update these results in a subsequent disclosure and update to this working paper.

Figure 2.1: TFP Increase from Equalizing Within-Industry Distortions



Note: The U.S. Manufacturing time series here is constructed using the Annual Survey of Manufactures, which is described in greater detail in the Data section of the paper and the accompanying data appendix.

costs in units of labor, then only a subset of the labor expenditures speak to labor used in production. An econometrician using the entirety of the reported labor expenditures would overstate the labor output elasticity. The resulting bias in measured productivity follows the bias patterns we characterize here.

To make these points more transparent, in section 2.2 we present a model of misallocation within a closed-economy multi-industry setting with establishment heterogeneity à la Melitz (2003). We allow returns to scale in production to vary across industries and incorporate distortions to inputs in the style of Hsieh and Klenow (2009). Section 2.3 formalizes two types of biases that might arise in this type of model: mismeasurement of labor elasticities in a constant RTS world, and mismeasurement of capital elasticities in a variable RTS world. In section 2.4 we introduce U.S. Census microdata, and throughout section 2.5 we discuss identification and the mapping of the model to data. Sections 2.6 and 2.7 present the empirical evidence on the size and direction of the biases, as well as time series measures of U.S. manufacturing misallocation. Section 2.8 concludes.

2.2 Model and Economic Intuition

We assume that the manufacturing sector is characterized by a representative establishment selling its output Y in a perfectly competitive market. This firm aggregates the output Y_i of I different industries using a Cobb-Douglas production technology with elasticities θ_i:

$$Y = \prod_{i=1}^{I} Y_i^{\theta_i}, \text{ with } \sum_{i=1}^{I} \theta_i = 1 \; . \tag{2.1}$$

Cost minimization by this aggregating firm implies that θ_i is also each industry's share of aggregate expenditure

$$P_i Y_i = \theta_i P Y \; , \tag{2.2}$$

where P_i is the price of an industry composite good, and P is the price of the final good

$$P = \prod_{i=1}^{I} \left(\frac{P_i}{\theta_i} \right)^{\theta_i} . \tag{2.3}$$

An industry aggregating firm produces Y_i from the output of N_i differentiated establishments via a constant-elasticity-of-substitution (CES) technology

$$Y_i = \left(\sum_{e=1}^{N_i} Y_{ie}^{\frac{\sigma-1}{\sigma}} \right)^{\sigma/(\sigma-1)} . \tag{2.4}$$

Each establishment in the industry produces value-added output Y_{ie} by combining its TFP A_{ie}, capital K_{ie} and labor L_{ie} in a Cobb-Douglas production function

$$Y_{ie} = A_{ie} K_{ie}^{\alpha_{K_i}} L_{ie}^{\alpha_{L_i}} \; , \tag{2.5}$$

where the industry level returns to scale β_i are the sum of the output elasticities α_{K_i} and α_{L_i}. Each establishment maximizes profits by taking as given the prices R and w from perfectly-competitive input markets. However, the effective cost of an input varies across establishments, with the $\tau_{K_{ie}}$ and $\tau_{L_{ie}}$ capturing this input-specific distortions for capital and labor, respectively.

$$\pi_{ie} = P_{ie}Y_{ie} - (1+\tau_{L_{ie}})wL_{ie} - (1+\tau_{K_{ie}})RK_{ie} \tag{2.6}$$

By internalizing the demand for its variety, the establishment charges a price that is a constant markup over its marginal cost. Note that the marginal cost under variable RTS depends on the scale of production:

$$P_{ie} = \left[\left(\frac{\sigma}{\sigma-1}\right)^{\beta_i} \left(P_i^{\sigma} Y_i\right)^{1-\beta_i} \left(\frac{R}{\alpha_{K_i}}\right)^{\alpha_{K_i}} \left(\frac{w}{\alpha_{L_i}}\right)^{\alpha_{L_i}} \right. \\ \left. \times \frac{(1+\tau_{K_{ie}})^{\alpha_{K_i}}(1+\tau_{L_{ie}})^{\alpha_{L_i}}}{A_{ie}} \right]^{1/(\beta_i+\sigma(1-\beta_i))} . \tag{2.7}$$

Within the confines of this model, there is a natural restriction on the returns to scale parameter. As in Basu and Fernald (1997), standard cost-minimization requires that the RTS parameter β_i be (weakly) less than the markup $\sigma/(\sigma-1)$. The returns to scale and the markup shape the price elasticities of supply and demand, respectively. The price elasticity of supply is increasing in the RTS parameter β_i: when RTS are sufficiently large, the supply curve becomes downward sloping. The restriction that β_i is smaller than the markup guarantees that a downward-sloping supply curve is not steeper than a downward-sloping demand curve. This restriction ensures that the willingness-to-pay reflected in the demand curve exceeds the cost of production embodied by the supply curve when establishments are deciding whether to produce. A rearrangement of this inequality guarantees that the often-recurring term $[\beta_i + \sigma(1-\beta_i)]$ is positive.

An establishment facing larger distortions uses less capital and labor.

$$K_{ie} \propto \left[\frac{A_{ie}^{\sigma-1}}{(1+\tau_{K_{ie}})^{[\beta_i+\sigma(1-\beta_i)]+\alpha_{K_i}(\sigma-1)}(1+\tau_{L_{ie}})^{\alpha_{L_i}(\sigma-1)}} \right]^{1/(\beta_i+\sigma(1-\beta))} \tag{2.8}$$

$$L_{ie} \propto \left[\frac{A_{ie}^{\sigma-1}}{(1+\tau_{K_{ie}})^{\alpha_{K_i}(\sigma-1)}(1+\tau_{L_{ie}})^{[\beta_i+\sigma(1-\beta_i)]+\alpha_{L_i}(\sigma-1)}} \right]^{1/(\beta_i+\sigma(1-\beta))} \tag{2.9}$$

Moreover, measured either in terms of physical output or the establishment's revenue share in the industry, a more distorted establishment is also smaller in size.

$$\frac{P_{ie}Y_{ie}}{P_iY_i} = \frac{\left[\dfrac{A_{ie}}{(1+\tau_{K_{ie}})^{\alpha_{K_i}}(1+\tau_{L_{ie}})^{\alpha_{L_i}}} \right]^{(\sigma-1)/(\beta_i+\sigma(1-\beta_i))}}{\displaystyle\sum_{e'=1}^{N_i} \left[\dfrac{A_{ie'}}{(1+\tau_{K_{ie'}})^{\alpha_{K_i}}(1+\tau_{L_{ie'}})^{\alpha_{L_i}}} \right]^{(\sigma-1)/(\beta_i+\sigma(1-\beta_i))}} \tag{2.10}$$

These distortions affect establishment choices by changing the marginal revenue gained from an additional unit of an input (e.g. $MRPK_{ie}$ for capital K_{ie}). In equilibrium, the marginal revenue product of an additional hired input equals the effective cost to the establishment of hiring the input. If an establishment faces barriers that make acquiring capital more expensive, then $(1+\tau_{K_{ie}})$ is high, and the establishment will only hire an additional unit of capital if its $MRPK_{ie}$ exceeds the cost $(1+\tau_{K_{ie}})R$. The same reasoning holds for all variable inputs in production.

$$MRPK_{ie} \triangleq MPK_{ie} \times P_{ie} \times \frac{\sigma-1}{\sigma} = \alpha_{K_i}\frac{Y_{ie}}{K_{ie}}P_{ie}\frac{\sigma-1}{\sigma} = (1+\tau_{K_{ie}})R \tag{2.11}$$

$$MRPL_{ie} \triangleq MPL_{ie} \times P_{ie} \times \frac{\sigma-1}{\sigma} = \alpha_{L_i}\frac{Y_{ie}}{L_{ie}}P_{ie}\frac{\sigma-1}{\sigma} = (1+\tau_{L_{ie}})w \tag{2.12}$$

To understand the impact of establishment-level distortions on the productivity of the industry as a whole, we need to aggregate the establishment choices. Combining input-market-clearing conditions with establishment input choices, we can show that each industry uses capital and labor in proportion to the industry's share of the national economy θ_i, the industry's input elasticity α_{X_i} for a given factor X, and in inverse proportion to that factor's average marginal revenue products across the industry's establishments $\overline{MRPX_i}$.

$$K_i = K\,\frac{\alpha_{K_i}\theta_i\frac{1}{\overline{MRPK_i}}}{\sum_{i'=1}^{I}\alpha_{K_{i'}}\theta_{i'}\frac{1}{\overline{MRPK_{i'}}}} \tag{2.13}$$

$$L_i = L\,\frac{\alpha_{L_i}\theta_i\frac{1}{\overline{MRPL_i}}}{\sum_{i'=1}^{I}\alpha_{L_{i'}}\theta_{i'}\frac{1}{\overline{MRPL_{i'}}}} \tag{2.14}$$

The average marginal revenue products are weighted by establishment size. In the absence of distortions, or if all establishments faced the same distortion,

$MRPX_{ie}$ would be equal across establishments and hence equal to the industry $\overline{MRPX_i}$. We revisit this point below when we define a counterfactual allocation of resources in which all establishments are equally distorted.

$$\frac{1}{\overline{MRPK_i}} = \sum_{f=1}^{N_i} \frac{1}{MRPK_{ie}} \frac{P_{ie}Y_{ie}}{P_iY_i} = \frac{1}{R} \sum_{f=1}^{N_i} \frac{1}{(1+\tau_{K_{ie}})} \frac{P_{ie}Y_{ie}}{P_iY_i} \tag{2.15}$$

$$\frac{1}{\overline{MRPL_i}} = \sum_{f=1}^{N_i} \frac{1}{MRPL_{ie}} \frac{P_{ie}Y_{ie}}{P_iY_i} = \frac{1}{w} \sum_{f=1}^{N_i} \frac{1}{(1+\tau_{L_{ie}})} \frac{P_{ie}Y_{ie}}{P_iY_i} \tag{2.16}$$

Industry output can now be expressed as

$$Y_i = A_i K_i^{\alpha_{K_i}} L_i^{\alpha_{L_i}} \ , \tag{2.17}$$

where A_i is the total factor productivity TFP_i of the industry. In thinking about how distortions affect industry productivity, we introduce notation based on Foster et al. (2008) and Hsieh and Klenow (2009) that distinguishes the productivity for producing a quantity of physical goods, $TFPQ_{ie}$, from the productivity for generating revenue, $TFPR_{ie}$.

$$TFPQ_{ie} \triangleq A_{ie} = \frac{Y_{ie}}{K_{ie}^{\alpha_{K_i}} L_{ie}^{\alpha_{L_i}}} \tag{2.18}$$

$$TFPR_{ie} \triangleq P_{ie}A_{ie} = \frac{P_{ie}Y_{ie}}{K_{ie}^{\alpha_{K_i}} L_{ie}^{\alpha_{L_i}}} \tag{2.19}$$

This distinction is helpful since two establishments with the same physical productivity $TFPQ_{ie}$ can have different revenue productivities $TFPR_{ie}$ if they face different distortions.

$$TFPR_{ie} = \left(\frac{\sigma}{\sigma-1}\right)^{\beta_i} \left(P_{ie}Y_{ie}\right)^{1-\beta_i} \left[\frac{MRPK_{ie}}{\alpha_{K_i}}\right]^{\alpha_{K_i}} \left[\frac{MRPL_{ie}}{\alpha_{L_i}}\right]^{\alpha_{L_i}} \tag{2.20}$$

$$TFPR_{ie} \propto \left[(1+\tau_{K_{ie}})^{\alpha_{K_i}}(1+\tau_{L_{ie}})^{\alpha_{L_i}} A_{ie}^{(\sigma-1)(1-\beta_i)}\right]^{1/(\beta_i+\sigma(1-\beta_i))} \tag{2.21}$$

Revenue productivity increases with the level of distortions, as the establishment's input bundle has to compensate for a large effective cost of hiring the inputs. Under decreasing returns to scale, higher physical productivity raises revenue productivity; under increasing returns to scale, higher physical productivity lowers revenue productivity. This differential impact of RTS on $TFPR_{ie}$ comes from the relationship between the RTS parameter, β_i, and the price elasticity of supply. With higher returns to scale come higher price elasticities. For a small increase in physical productivity, price declines much more strongly under increasing returns to scale. The decline in equilibrium price can sufficiently offset the increase in output from higher A_{ie} so that the average revenue productivity $TFPR_{ie}$ declines under increasing RTS.

We can define an industry revenue productivity following the establishment definition:

$$\overline{TFPR}_i \triangleq P_i A_i = \left(\frac{\sigma}{\sigma-1}\right)^{\beta_i} \left(P_i Y_i\right)^{1-\beta_i} \left[\frac{\overline{MRPK}_i}{\alpha_{K_i}}\right]^{\alpha_{K_i}} \left[\frac{\overline{MRPL}_i}{\alpha_{L_i}}\right]^{\alpha_{L_i}} . \tag{2.22}$$

This formulation of industry revenue productivity allows us to write industry TFP_i as CES aggregate of establishment physical productivity A_{ie}, weighted by the difference between industry and establishment revenue productivity $\overline{TFPR_i}/TFPR_{ie}$.

$$TFP_i = P_i A_i \frac{1}{P_i} = \overline{TFPR}_i \frac{1}{P_i} = \left[\sum_{e=1}^{M_i} \left(A_{ie} \frac{\overline{TFPR}_i}{TFPR_{ie}} \right)^{\sigma-1} \right]^{1/(\sigma-1)} \tag{2.23}$$

The weight captures the establishment's size, as well as the deviations of its marginal revenue products from their respective industry averages.

$$\begin{aligned} \frac{\overline{TFPR}_i}{TFPR_{ie}} &= \left(\frac{P_i Y_i}{P_{ie} Y_{ie}} \right)^{1-\beta_i} \left[\frac{\overline{MRPK}_i}{MRPK_{ie}} \right]^{\alpha_{K_i}} \left[\frac{\overline{MRPL}_i}{MRPL_{ie}} \right]^{\alpha_{L_i}} \\ &\propto \left[\frac{1}{(1+\tau_{K_{ie}})^{\alpha_{K_i}} (1+\tau_{L_{ie}})^{\alpha_{L_i}}} \frac{1}{A_{ie}^{(\sigma-1)(1-\beta)}} \right]^{1/(\beta_i + \sigma(1-\beta_i))} \end{aligned} \tag{2.24}$$

More distorted establishments have smaller weights. Consequently, the correlation of productivity and distortion is important for measuring gains from equalizing the distortions faced by different establishments within the industry. If more productive establishments are also more distorted, then equalizing distortions would give larger weights to the more productive establishments in the counterfactual. This tilting of weights toward more productive establishments would translate to large TFP gains from reallocating inputs.

More formally, if all establishments within an industry face the same distortions, so that $\tau = \overline{\tau}$, then the establishment weights for calculating industry TFP_i

simplify in the following manner:

$$\left.\frac{\overline{TFPR_i}}{TFPR_{ie}}\right|_{\tau=\bar{\tau}} = \left(\left.\frac{P_iY_i}{P_{ie}Y_{ie}}\right|_{\tau=\bar{\tau}}\right)^{1-\beta_i} = \left[\frac{\sum_{e'=1}^{N_i} A_{ie'}^{\frac{\sigma-1}{\beta_i+\sigma(1-\beta_i)}}}{A_{ie}^{\frac{(\sigma-1)}{\beta_i+\sigma(1-\beta_i)}}}\right]^{1-\beta_i} . \tag{2.25}$$

Note that under constant returns to scale $\beta_i = 1$ and $TFPR_{ie}$ is identical across all establishments. This equality is at the center of the intuition used in Hsieh and Klenow (2009)intuition: "A key result we exploit is that *revenue* productivity…should be equated across firms in the absence of distortions. To the extent revenue productivity differs across firms, we can use it to recover a measure of firm-level distortions." Note, however, that if returns to scale in an industry are not constant, then revenue productivity can vary across undistorted establishments. As a result, there is not a direct mapping between the variance of TFPR and the misallocation within industry. To calculate the gains from eliminating distortions, the econometrician has to calculate the counterfactual weight from equation (2.25) for each establishment.

For every industry i, we then define misallocation as Φ_i, the net gain to industry TFP from equalizing distortions across establishments within the industry:

$$\Phi_i = \frac{TFP_i|_{\tau=\bar{\tau}}}{TFP_i} - 1 = \frac{\left[\sum_{e=1}^{N_i}\left(A_{ie}\left.\frac{\overline{TFPR_i}}{TFPR_{ie}}\right|_{\tau=\bar{\tau}}\right)^{\sigma-1}\right]^{1/(\sigma-1)}}{\left[\sum_{e=1}^{N_i}\left(A_{ie}\frac{\overline{TFPR_i}}{TFPR_{ie}}\right)^{\sigma-1}\right]^{1/(\sigma-1)}} - 1 . \tag{2.26}$$

The misallocation for all of U.S. manufacturing in a given year is then:

$$\Phi = \sum_{i \in I} \theta_i \Phi_i \ , \tag{2.27}$$

where θ_i is industry i's revenue share in the manufacturing sector.

2.3 Measurement Biases

Before moving to the data, we first formalize two biases that can arise with mismeasurement of production functions. First, we consider the case where an econometrician in a constant RTS world mismeasures the labor elasticity α_{L_i} for a given industry. Second, we consider the case where an econometrician in a variable RTS world looks at the data through the lens of constant returns and incorrectly uses $1-\alpha_{L_i}$ for the capital elasticity α_{K_i}.

2.3.1 Mismeasured Labor Elasticity Under Constant Returns to Scale

For $Y_{ie} = A_{ie} K_{ie}^{1-\alpha_{L_i}} L_{ie}^{\alpha_{L_i}}$, a constant RTS version of the production function in equation (2.5), what if the econometrician incorrectly estimates $\widehat{\alpha}_{L_i} = \gamma_i \alpha_{L_i}$? When $\gamma_i > 1$, then the labor share in this industry is overstated, and the capital share $1-\widehat{\alpha}_{L_i}$ is understated. The distortions would then be estimated as:

$$\begin{aligned}
(\widehat{1+\tau_{L_{ie}}}) &= \gamma_i (1+\tau_{L_{ie}}) \\
(\widehat{1+\tau_{K_{ie}}}) &= \frac{1-\gamma\alpha_{L_i}}{1-\alpha_{L_i}}(1+\tau_{K_{ie}})
\end{aligned}$$

Note that each distortion is mismeasured by a proportional, industry-specific constant. Hence, despite mismeasuring the level of the distortion, the econometrician can correctly calculate the distortion *relative* to an industry average. More specifically, for a given input X,

$$\frac{\widehat{1+\tau_{X_{ie}}}}{(\overline{1+\tau_{X_i}})} = \frac{1+\tau_{X_{ie}}}{(\overline{1+\tau_{X_i}})} \ .$$

However, using the incorrect production function, the econometrician would incorrectly infer productivity $\widehat{A_{ie}}$ as follows:

$$\begin{aligned} \widehat{A_{ie}} &= A_{ie} \left(\tfrac{K_{ie}}{L_{ie}} \right)^{\alpha_{L_i}(\gamma_i - 1)} \\ \widehat{A_{ie}} &\propto A_{ie} \left(\frac{(1+\tau_{L_{ie}})}{(1+\tau_{K_{ie}})} \right)^{\alpha_{L_i}(\gamma_i - 1)} \end{aligned} \tag{2.28}$$

In short, if she overstates α_{L_i} so that $\gamma_i > 1$, then the econometrician induces a spurious positive correlation between productivity and the capital-labor ratio: she overestimates the productivity of establishments with higher capital-labor ratios. From the second expression in (2.28), we can state the bias in a slightly different way. If the econometrician overstates α_{L_i}, then she overstates productivity for establishments facing large labor distortions relative to capital distortions.

The impact of these spurious correlations on measures of misallocation depends on the underlying correlations between productivity and the capital-labor ratio. To see this more clearly, we define an average capital-labor ratio in the industry in the following manner:

$$\frac{\widetilde{K_{ie}}}{L_{ie}} = \frac{1-\alpha_{L_i}}{\alpha_{L_i}} \frac{w}{R} \frac{\overline{(1+\tau_{L_i})}}{\overline{(1+\tau_{K_i})}} \, . \tag{2.29}$$

Note that this expression includes the ratio of the average labor and the average capital distortions in the industry. By Jensen's inequality, this ratio need not coincide with the average ratio of the labor and capital distortion. Therefore, the expression in (2.29) is equal to the weighted average of the capital-labor ratio across establishments only when the two distortions are uncorrelated. While more general correlation structures do away with this equality, the average in (2.29) always maps neatly into a comparison of the estimated industry misallocation $\widehat{\Phi}_i$ and the true underlying misallocation Φ:

$$\frac{\widehat{\Phi}_i}{\Phi} = \frac{\left[\sum_{e=1}^{N_i} \left\{ \left(\frac{\frac{K_{ie}}{L_{ie}}}{\frac{\widetilde{K_{ie}}}{L_{ie}}} \right)^{\alpha_{L_i}(\gamma_i - 1)} A_{ie} \right\}^{\sigma-1} \right]^{1/(\sigma-1)}}{\left[\sum_{e=1}^{N_i} A_{ie}^{\sigma-1} \right]^{1/(\sigma-1)}} \, . \tag{2.30}$$

To fix ideas, consider the case where the labor elasticity is overstated so that $\gamma_i > 1$. If productivity A_{ie} is positively correlated with the capital-labor ratio, then the estimated misallocation $\widehat{\Phi}_i$ would overstate true misallocation Φ_i. More specifically, high productivity establishments would have capital-labor ratios in excess of the average, so their productivity weights in the numerator of (2.30) would be greater than one; the weights for less productive establishments would be smaller than one. This re-weighting of productivity with relative capital-labor ratios leads to a misallocation measurement bias.

We can also express the bias in terms of relative distortions. The productivity weights in the numerator of (2.30) are also the relative labor-capital distortions. Hence, if more productive establishment systematically face larger relative distortions in hiring labor than capital, then the measurement bias would be positive. The below expression formalizes this restatement of the bias.

$$\frac{\widehat{\Phi}_i}{\Phi} = \frac{\left[\sum_{e=1}^{N_i}\left\{\left(\frac{\frac{(1+\tau_{L_{ie}})}{(1+\tau_{K_{ie}})}}{\frac{(1+\tau_{L_i})}{(1+\tau_{K_i})}}\right)^{\alpha_{L_i}(\gamma_i-1)} A_{ie}\right\}^{\sigma-1}\right]^{1/(\sigma-1)}}{\left[\sum_{e=1}^{N_i} A_{ie}^{\sigma-1}\right]^{1/(\sigma-1)}}$$

2.3.2 Mismeasured Capital Elasticity Under Variable Returns to Scale

A common implementation of the constant returns-to-scale production function from equation (2.5) entails estimating a labor elasticity α_{L_i} and assigning the residual $1-\alpha_{L_i}$ as the capital elasticity. If this industry's returns to scale in production are not constant, then this $\widehat{\alpha_{K_i}} = 1-\alpha_{L_i}$ mismeasures the true capital elasticity α_{K_i}. With a correctly-estimated labor elasticity, the labor distortion is still correctly measured. However, overstating the capital elasticity, so that $1-\alpha_{L_i}$ exceeds α_{K_i}, leads the econometrician to overstate the capital distortion:

$$\widehat{(1+\tau_{K_{ie}})} = \frac{1-\alpha_{L_i}}{\alpha_{K_i}}(1+\tau_{K_{ie}}) \ .$$

Once again, despite mismeasuring the level of the distortion, the econometrician can correctly calculate the capital distortion *relative* to an industry average:

$$\frac{\widehat{1+\tau_{K_{ie}}}}{\overline{(1+\tau_{K_i})}} = \frac{1+\tau_{K_{ie}}}{\overline{(1+\tau_{K_i})}} \ .$$

However, if the assumption of constant returns to scale overstates the actual returns to scale, so that $\alpha_{K_i} + \alpha_{L_i} = \beta_i < 1$, then the econometrician understates productivity

$$\widehat{A_{ie}} = \frac{A_{ie}}{K_{ie}^{1-\beta_i}} \ . \qquad (2.31)$$

While the erroneous production function leads the econometrician to understate productivity for all establishments, the degree by which productivity is understated increases in the establishment's capital stock. We can highlight two important forces shaping the mismeasurement of misallocation by rewriting (2.31) in terms of establishment-specific fundamentals:

$$\widehat{A_{ie}} \propto A_{ie}^{\frac{1}{\beta_i+\sigma(1-\beta_i)}}(1+\tau_{L_{ie}})^{\frac{\alpha_{L_i}(\sigma-1)(1-\beta_i)}{\beta_i+\sigma(1-\beta_i)}}(1+\tau_{K_{ie}})^{\frac{[\sigma-\alpha_{L_i}(\sigma-1)](1-\beta_i)}{\beta_i+\sigma(1-\beta_i)}} \ .$$

First, when $\beta_i < 1$, the exponents on both distortions are positive. In other words, when the econometrician overstates the returns to scale, she induces a spurious positive correlation between productivity and the distortions, and perceives more distorted establishments as more productive. Second, the exponent on the productivity term A_{ie} is less than one; productivity is understated for all establishments, but, holding distortions constant, productivity is understated more for the more productive establishments.

These two forces shape the bias in measured misallocation. By overstating the returns to scale, the econometrican mistakenly perceives more distorted establishments as more productive. She thinks that industry productivity could be significantly improved if only the more productive firms could be rid of their disproportionately large distortions. This mistaken, or overstated, belief results in an upward bias in measured misallocation. The second force leads to smaller and more compressed estimates of productivity. If productivity and distortions are indeed positively correlated, then this compression induces a downward bias in measured productivity.

$$\frac{\widehat{\Phi}_i}{\Phi} = \frac{\left[\sum_{e=1}^{N_i} \left[\frac{A_{ie}}{(1+\tau_{K_{ie}})^{\alpha_{K_i}}(1+\tau_{L_{ie}})^{\alpha_{L_i}}}\right]^{\frac{\sigma-1}{\beta_i+\sigma(1-\beta_i)}} \left[(1+\tau_{K_{ie}})^{1-\alpha_{L_i}}(1+\tau_{L_{ie}})^{\alpha_{L_i}}\right]^{\sigma-1}\right]^{\frac{1}{\sigma-1}}}{\left[\sum_{e=1}^{N_i} A_{ie}^{\frac{\sigma-1}{\beta+\sigma(1-\beta)}}\right]^{\frac{1}{\sigma-1}}}$$

$$\times \frac{\left[\frac{1}{(\overline{1+\tau_{K_i}})}\sum_{e=1}^{N_i}\left[\frac{A_{ie}}{(1+\tau_{K_{ie}})^{\alpha_{K_i}}(1+\tau_{L_{ie}})^{\alpha_{L_i}}}\right]^{\frac{\sigma-1}{\beta+\sigma(1-\beta)}}\right]^{1-\beta_i}}{\left[\sum_{e=1}^{N_i} A_{ie}^{\frac{\sigma-1}{\beta+\sigma(1-\beta)}}\right]^{1-\beta_i}} \tag{2.32}$$

2.4 Data

We employ two data sets provided by the U.S. Census Bureau to measure misallocation in U.S. manufacturing. The first is the Census of Manufactures (CMF), which is conducted every five years (during years ending with “2” and “7”) and contains information about all manufacturing establishments in the U.S. The second is the Annual Survey of Manufactures (ASM), which is conducted in all non-Census years and covers a subset of the establishments covered by the CMF. Establishments with at least 250 employees are included in every ASM while plants with fewer employees are rotated in and out with random sampling every five years. On average, the ASM surveys 50,000–65,000 establishments selected from the approximately 350,000 establishments in the CMF. From these datasets, we obtain information such as total value of shipments, value added, capital expenditures, production and non-production workers, material costs and the relevant price deflators. In addition, we obtain public data on depreciation rates from the Bureau of Labor Statistics (BLS) and the real rates of return on capital from the Bureau of Economic Analysis (BEA).

Our sample period spans the years from 1977 to 2007. We exclude establishments whose information is imputed from administrative records, as well as those with missing information in any of the factor variables. We also exclude industries that contain fewer than five establishments in any given year. To remove outliers, we trim establishments whose measured physical productivity or TFPR is five times larger than the industry mean in a given year, as well as those in the one percent tails.

Over the course of the sample period, industry classification in the U.S. changed from the Standard Industrial Classification (SIC) system to the NAICS (North American Industrial Classification System). We use the Fort-Klimek SIC-NAICS concordance to map the changes of industrial codes across years. This concordance provides each establishment with a time-consistent NAICS 2002 code. For a small number of the 400+ 6-digit NAICS industries, we identify discontinuities in industry employment and establishment counts around the years where industry classification changed. If the NAICS dictionaries suggest that the industries in question are cross-listed, we attempt to merge them into a single industry. When the merging eliminates discontinuities, we use the merged industries; otherwise, we exclude the industries from analysis.

2.5 Mapping the Model to Data

As we highlighted in the introduction, and as previous authors stated, this family of models struggles to separately identify the production function parameters from the distortions faced by the establishments. Our resolution to this problem entails two steps. First, we show that we do not need to identify the full model in order to use the model structure to measure misallocation. Specifically, we show that to measure misallocation, the econometrician needs only the relative level of the distortions, and not the absolute level; in this manner we eliminate the level of the average industry distortion as a parameter needed for this exercise. Second, we highlight the fact that the model is agnostic about the interpretation of the distortions. From the model's perspective, there is one distortion for each of the two establishment first-order conditions. As a result, there are multiple model-consistent ways of specifying an establishment profit function: for instance, the distortions could be on revenue and capital, or, as we model them, on labor and capital. We show that the latter choice of the profit function, and the accompanying interpretation of the distortions, can help identify parameters for measuring misallocation.

To emphasize the first point, we return to the expression for misallocation in equation (2.26), and note that there are three model objects that the econometrician needs to measure misallocation: physical productivity (A_{ie}), the relative revenue productivity (TFPR ratio), and the counterfactual relative revenue productivity (TFPR ratio when all distortions are equalized). Of these three objects, only the second, the relative revenue productivity, requires knowledge of the distortions faced by establishments.

Proposition 5. The relative revenue productivity term, $\overline{TFPR}_i/TFPR_{ie}$, can be rewritten as a function of the *relative* distortions on factor inputs, i.e. an establishment's input distortions relative to its industry's average.

$$\frac{\overline{TFPR}_i}{TFPR_{ie}} \propto \left\{ \left[\frac{\overline{1+\tau_{K_i}}}{1+\tau_{K_{ie}}} \right]^{\alpha_{K_i}} \left[\frac{\overline{1+\tau_{L_i}}}{1+\tau_{L_{ie}}} \right]^{\alpha_{L_i}} \frac{1}{A_{ie}^{(\sigma-1)(1-\beta)}} \right\}^{1/(\beta_i+\sigma(1-\beta_i))}$$

Proof is in Appendix B.2.1.

With this proposition, we now show how the specification of a profit function can help separately identify the production function parameters, and hence productivity, as well as relative distortions. To convey the identification concisely, we focus on identifying the labor output elasticity, and the relative labor distortions. Consider the schematic presented in Table 2.1. Across all three model mappings, we have access to the same U.S. Census observations on an individual establishment.

Column (1) provides the mapping using the profit function in which the distortions are on the establishment's revenue and capital input. This is perhaps the most common choice in the literature, allowing authors to interpret the first distortion as a distortion to establishment size, and the second as a distortion to the relative marginal products of capital and labor. In this implementation, the econometrician interprets the data on *Salaries and Wages* and *Value Added* as the distortion-exclusive objects $w_i L_{ie}$ and $P_{ie} Y_{ie}$. However, to obtain the labor output elasticity from the establishment's first-order condition for labor, the econometrician needs the distortion-inclusive $(1 - \tau_{Y_{ie}})P_{ie}Y_{ie}$. In short, by not knowing the revenue distortion faced by the establishment, the econometrician mismeasures the establishment's marginal cost and hence the denominator of the labor output elasticity in column (1). Without a correctly-measured production function parameter, the econometrician induces the biases detailed earlier in the paper.

Column (2) shows that we can identify the production function elasticity with a different, model-consistent profit function. If we interpret the distortions as falling on the labor and capital inputs, we can interpret the same U.S. Census data as corresponding to $(1 + \tau_{L_{ie}})w_i L_{ie}$ and $P_{ie}Y_{ie}$. In this context, the distortions directly affect the relative input prices of the establishment, and the labor distortion now captures establishment-specific variations in the wage paid. With this assumption, the econometrician has the distortion-inclusive data to correctly measure the elasticity $\widehat{\alpha_{L_i}}$. However, she would not be able to measure the level, absolute or relative, of the labor distortion. The standard approach to inferring the labor distortion using the first-order condition requires data on the distortion-exclusive $w_i L_{ie}$. Attempting to plug the distortion-inclusive $(1 + \tau_{L_{ie}})w_i L_{ie}$ into the expression would lead to a measured distortion of unity in the model. As a result, this mapping can identify the production-function parameter, but not the relative distortions.

Column (3) shows one way in which the identification problem can be resolved. Using the same profit function as in column (2), the econometrician would again interpret expenditures on labor in the data as distortion-inclusive. In addition, she will also leverage an additional establishment-level variable, labor hours (L_{ie}). As before, she will correctly identify the labor output elasticity. Now, by comparing

Table 2.1: Identification of Labor Output Elasticity and Distortions

	(1) Unidentified Mapping I	(2) Unidentified Mapping II	(3) Identified Mapping
Profit function	$(1-\tau_{Y_{ie}})P_{ie}Y_{ie} - w_iL_{ie}$ $-(1+\tau_{K_{ie}})R_iK_{ie}$	$P_{ie}Y_{ie} - (1+\tau_{L_{ie}})w_iL_{ie}$ $-(1+\tau_{K_{ie}})R_iK_{ie}$	$P_{ie}Y_{ie} - (1+\tau_{L_{ie}})w_iL_{ie}$ $-(1+\tau_{K_{ie}})R_iK_{ie}$
<u>CMF/ASM Data</u>			
Salaries & Wages	w_iL_{ie}	$(1+\tau_{L_{ie}})w_iL_{ie}$	$(1+\tau_{L_{ie}})w_iL_{ie}$
Value Added	$P_{ie}Y_{ie}$	$P_{ie}Y_{ie}$	$P_{ie}Y_{ie}$
Hours	L_{ie}	L_{ie}	L_{ie}
Labor Output Elasticity ($\widehat{\alpha_{L_i}}$)	$\dfrac{\sum_{e=1}^{M_i} w_iL_{ie}}{\frac{\sigma-1}{\sigma}\sum_{e=1}^{M_i}(1-\tau_{Y_{ie}})P_{ie}Y_{ie}}$ (mismeasured)	$\dfrac{\sum_{e=1}^{M_i}(1+\tau_{L_{ie}})w_iL_{ie}}{\frac{\sigma-1}{\sigma}\sum_{e=1}^{M_i} P_{ie}Y_{ie}}$	$\dfrac{\sum_{e=1}^{M_i}(1+\tau_{L_{ie}})w_iL_{ie}}{\frac{\sigma-1}{\sigma}\sum_{e=1}^{M_i} P_{ie}Y_{ie}}$
Distortion, Level	$\widehat{(1-\tau_{Y_{ie}})} = \dfrac{\frac{w_iL_{ie}}{\frac{\sigma-1}{\sigma}P_{ie}Y_{ie}}}{\widehat{\alpha_{L_i}}}$ (mismeasured)	$\widehat{(1+\tau_{L_{ie}})} = \dfrac{\widehat{\alpha_{L_i}}}{\frac{(1+\tau_{L_{ie}})w_iL_{ie}}{\frac{\sigma-1}{\sigma}P_{ie}Y_{ie}}} = 1$ (mismeasured)	$\widehat{(1+\tau_{L_{ie}})} = \dfrac{\widehat{\alpha_{L_i}}}{\frac{w_iL_{ie}}{\frac{\sigma-1}{\sigma}P_{ie}Y_{ie}}}$ (mismeasured)
Distortion, Relative	$\dfrac{\widehat{(1-\tau_{Y_{ie}})}}{\overline{(1-\tau_{Y_i})}} = \dfrac{Average\left(\frac{P_{ie}Y_{ie}}{w_iL_{ie}}\right)}{\frac{P_{ie}Y_{ie}}{w_iL_{ie}}}$	$\dfrac{\widehat{(1+\tau_{L_{ie}})}}{\overline{(1+\tau_{L_i})}} = 1$ (mismeasured)	$\dfrac{\widehat{(1+\tau_{L_{ie}})}}{\overline{(1+\tau_{L_i})}} = \dfrac{Average\left(\frac{L_{ie}}{P_{ie}Y_{ie}}\right)}{\frac{L_{ie}}{P_{ie}Y_{ie}}}$

the ratio of labor hours to revenue across the establishments, the econometrician can identify the relative distortion in the industry. This comparison works in the model as all parameters common to the industry – including the wage, the labor elasticity, and the elasticity of substitution – cancel out. In a manner that will prove helpful for comparison across models, this relative distortion is independent of the production function parameters. In short, while this approach cannot identify all the model parameters – notably the absolute level of the distortions – it can identify the production-function parameters and the relative distortions necessary for measuring misallocation. We explain this mapping in more detail in the following subsections.

2.5.1 Constant Returns to Scale

For the model with constant returns to scale, we use the establishment first-order condition for labor to estimate the output elasticity for labor. Taking a sum across all establishments in an industry and rearranging, the labor elasticity is

$$\alpha_{L_i} = \frac{\sum\limits_{e \in N_i} (1 + \tau_{L_{ie}}) w L_{ie}}{\sum\limits_{e \in N_i} \frac{\sigma - 1}{\sigma} P_{ie} Y_{ie}} = \frac{\sum\limits_{e \in N_i} \text{Salaries and Wages}_{ie}}{\sum\limits_{e \in N_i} \frac{\sigma - 1}{\sigma} \text{Value Added}_{ie}} . \tag{2.33}$$

We assume that the observed *Salaries and Wages* paid by each establishment are measured inclusive of establishment-specific wages and imply an establishment-specific distortion $1 + \tau_{L_{ie}}$. Given the assumption of constant returns to scale, the output elasticity for capital α_{K_i} is $1 - \alpha_{L_i}$.

With the production function parameters identified, we can infer physical productivity A_{ie} as in equation (2.18). The key challenge is that Census data does not report physical quantities of output, so we have to rely on the model for a mapping between revenue $P_{ie}Y_{ie}$ and output Y_{ie}. Following Hsieh and Klenow (2009), we use the industry aggregating firm's cost-minimization for the second equality below:

$$A_{ie} = \frac{Y_{ie}}{K_{ie}^{\alpha_{K_i}} L_{ie}^{\alpha_{L_i}}} = \frac{\kappa_i (P_{ie}Y_{ie})^{\frac{\sigma-1}{\sigma}}}{K_{ie}^{\alpha_{K_i}} L_{ie}^{\alpha_{L_i}}} = \frac{\kappa_i (\text{Value Added}_{ie})^{\frac{\sigma-1}{\sigma}}}{\text{Capital Stock}_{ie}^{\alpha_{K_i}} \text{Hours}_{ie}^{\alpha_{L_i}}} \, .$$

We normalize the industry-coefficient κ_i to one. For the purpose of measuring misallocation, this normalization is inconsequential. This measure of productivity appears in both the numerator and the denominator of the misallocation expression Φ in equation (2.26), and hence the industry-wide κ_i cancels out in the ratio of counterfactual and actual industry TFP. We can also see this cancellation in the constant and variable RTS bias expressions (2.30) and (2.32).

As we emphasized at the start of this section, we need only measure relative distortions to measure misallocation. Calculating the relative distortion allows us to eliminate all the industry-specific parameters, including the wage w_i, the labor elasticity α_{L_i} and the elasticity of substitution σ. In doing so, we need only calculate the following ratio:

$$\frac{(1+\tau_{L_{ie}})}{\overline{(1+\tau_{L_i})}} = \frac{\mathit{Average}\left(\frac{L_{ie}}{P_{ie}Y_{ie}}\right)}{\frac{L_{ie}}{P_{ie}Y_{ie}}} = \frac{\mathit{Industry\ Average}\left(\frac{\text{Hours}_{ie}}{\text{Value Added}_{ie}}\right)}{\frac{\text{Hours}_{ie}}{\text{Value Added}_{ie}}} \, . \tag{2.34}$$

To identify the capital distortions, we proceed in the same manner, and rearrange the first-order condition in the following manner:

$$\frac{(1+\tau_{K_{ie}})}{(\overline{1+\tau_{K_i}})} = \frac{Average\left(\frac{K_{ie}}{P_{ie}Y_{ie}}\right)}{\frac{K_{ie}}{P_{ie}Y_{ie}}} = \frac{Industry\ Average\left(\frac{\text{Capital Stock}_{ie}}{\text{Value Added}_{ie}}\right)}{\frac{\text{Capital Stock}_{ie}}{\text{Value Added}_{ie}}} .$$

With the above model objects, we now have all the parameters we need to calculate misallocation under the assumption of constant returns to scale.

2.5.2 Variable Returns to Scale

For the variable returns to scale model, the labor elasticity and both relative distortions are estimated as in the previous subsection. Note that, as per Table 2.1, the measures of relative distortions are independent of the production-function parameters. The key challenge to implementing the variable returns to scale model is the estimation of a capital elasticity. To estimate the elasticity α_{K_i}, we take natural logarithms of the production function and arrive at the following regression framework:

$$\begin{aligned} y_{ie,t,j} - \alpha_{L_i} l_{ie,t,j} &= \alpha_{K_i} k_{ie,t,j} + a_{ie,t,j} \\ y_{ie,t,j} - \alpha_{L_i} l_{ie,t,j} &= \alpha_{K_i} k_{ie,t,j} + \varepsilon_{ie,t,j} \end{aligned} \tag{2.35}$$

where $y_{ie,t}$, $k_{ie,t}$, $l_{ie,t}$ and $a_{ie,t}$ are natural logarithms of physical output, capital stock, labor hours and TFP, respectively.

Our current estimates of α_{K_i} come from industry-by-industry regressions of the form (2.35) with establishment-level fixed effects. Since the establishment-level physical productivity ($a_{ie,t}$) is unobserved, we face an omitted variable problem. In short, if the observed inputs are chosen as a function of the unobserved productivity that is not accounted for by establishment fixed effects, then this endogeneity problem would return biased estimates of the capital elasticities.

To address the endogeneity problem in a future version of this paper, we need a more robust manner of accounting for unobserved changes in physical productivity. Some papers in this literature have turned to the control-function methods for estimating production functions, using the tools proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003). In essence, this literature proposes using a second equation, often one coming from a cost-minimization problem, to render unobserved productivity observable. Key assumptions required for this substitution are that this second equation can (1) be inverted to express unobserved productivity as a function of the other variables, and that (2) unobserved productivity is the only unobserved object in this second equation. We think that this family of misallocation models is not compatible with this second assumption. For instance, the Olley and Pakes (1996) inversion of the investment function would require that the investment choice depend only on unobserved productivity; however, in this model of misallocation, the investment choice would also depend on unobserved distortions in the capital markets. Similarly, the Levinsohn and Petrin (2003) use of a first-order condition for intermediate inputs would require assuming that establishments face distortions in their choices of capital and labor, but not in the market for intermediate inputs. In light of the inconsistency between the assumptions of our model and these estimation strategies, we turn to a literature on dynamic panel estimation.

Arellano and Bond (1991) and Blundell and Bond (2000) have proposed panel estimators that can control for unobservable effects at the level of an establishment-year. In short, these estimators trade off the control-function approach's second assumption for more structure on the unobserved productivity process. These papers derive moment conditions with which the econometrician can jointly estimate the parameters of the productivity process and the production function using the Generalized Method of Moments (GMM). We are currently implementing these procedures, and hope to have the updated returns to scale estimates in the next disclosure.

2.6 Productivity and Distortions in the Data

We begin by summarizing the production-function parameters estimated at the NAICS-6 level for the models on display in Figure 2.1 from the introduction. The first column of Table 2.4 shows that the labor output elasticity in the median industry is 0.61, with an interquartile range between 0.47 and 0.69. The second column contains estimates of returns to scale, comprising the labor elasticity from the first column plus the OLS estimates of the capital elasticity estimated using equation (2.35). These estimates suggest strongly decreasing returns to scale in production: the median returns to scale is 0.85.

We make two notes about these estimates. First, the labor expenditures re-

Table 2.2: Summary of Estimated Returns to Scale Coefficients

	Labor Output Elasticity α_{L_i}	Returns to Scale $\beta_i = \alpha_{L_i} + \alpha_{K_i}^{OLS}$
25th Percentile	0.4742	0.7475
50th Percentile	0.6080	0.8504
75th Percentile	0.6884	0.9311

ported in the U.S. Census of Manufactures and the Annual Survey of Manufactures (e.g. salaries and wages) do not include expenditures on benefits for workers. Using unpublished estimates from the National Compensation Survey run by the Bureau of Labor Statistics, we construct adjustment factors reflecting the ratio of (hourly wage plus hourly benefits) relative to (hourly wage). Since the survey has a relatively small sample, we are able to construct these adjustment factors at the NAICS-3 level as 5-year averages overlapping with the 5-year census periods. The adjustment factors range from 1.35 to 1.92, with a median of 1.52. We provide more details about these in the data appendix.

Second, the labor elasticity in equation (2.33) depends on the elasticity of substitution σ. Following the convention in this literature, we make the assumption that the profits of the monopolistically-competitive establishments in the model are shared between owners of labor and capital in proportion to the cost shares of labor and capital in production. By assuming that the total labor expenditure include the direct payments to labor as well as labor's share of the profits, the labor elasticity can then be estimated as the ratio of labor expenditures to value added, independent of the elasticity σ. The cost of this assumption is fealty to the model. The benefit is twofold: the production-function parameters do not depend on the parameter σ, which we cannot estimate industry by industry. Moreover, as some papers use values of σ as low as 3, the labor elasticity estimates, without that assumption, would be 1.5 times greater than the ones listed in column 1. Under that implementation, many industries would have labor elasticities in excess of unity, making constant RTS models impossible to implement.

Establishment-Level Biases

In the process of characterizing the aggregate bias in measured misallocation, we first highlight the source of this bias: spurious correlations between productivity and distortions at the establishment level. In a constant RTS world, equation (2.28) predicts that when the labor elasticity is overstated, the econometrician induces a spurious positive correlation between productivity and the capital-labor ratio. Establishments with higher capital-labor ratios appear more productive, even when controlling for true physical productivity. Conversely, when the labor elasticity is understated, establishments with higher capital-labor ratios appear less productive.

Panel A of Table 2.3 documents this bias using a regression of the following form:

$$ln\left(TFPQ_{ie,t}^{Unidentified}\right) = a\ln\left(\frac{K_{ie,t}}{L_{ie,t}}\right) + b\ln\left(TFPQ_{ie,t}^{Identified}\right) + \psi_{it} \ ,$$

where $TFPQ_{ie,t}$ is the physical productivity A_{ie} from either the identified model where production functions vary by industry, or from the "unidentified" model where a single production function is applied to all industries. Further, $K_{ie,t}/L_{ie,t}$ is the capital-labor ratio and ϕ_{it} are industry-times-year fixed effects. All variables are normalized by demeaning them with their respective industry averages and then dividing by their industry standard deviations. Looking across all industries, the first coefficient in column (1) states that, controlling for establishment productivity in the identified model, a log K/L ratio that is one standard deviation above the mean is associated with an inferred productivity that is 0.1161 standard deviations below the mean. Columns (2) and (3) split the sample of industries into those where the labor elasticity is understated and those where it is overstated. As per the model predictions, the correlation in column (2) is positive: productivity is overstated for high-K/L establishments when α_{L_i} is overstated. Conversely, productivity is understated for high-K/L establishments when α_{L_i} is understated, as per column (3).

Panel B documents these spurious correlations across constant and variable RTS models. Instead of the log K/L ratio, panel B focuses on a geometric average of the relative distortions faced by an establishment, where the weights are the labor and capital elasticities from the variable RTS model. As per equation (2.31), we should expect overstatements of returns to scale to lead to overstatements of productivity, and vice versa. As our current estimates of RTS suggest that most industries have decreasing returns to scale in production, column (1) suggests that, on average, a one standard deviation increase in the geometric distortion is correlated with a 0.3770 standard deviation increase in constant RTS productivity, even controlling for variable RTS productivity. Splitting the sample into industries with overstated and understated RTS, we see a pattern consistent with the bias patterns suggested

Table 2.3: Measured Physical Productivity and Distortions

Panel A: Constant Returns to Scale, Identified vs Unidentified Bias

	Normalized log TFPQ, Unidentified Model		
	(1)	(2)	(3)
Normalized log K/L Ratio	−0.1161	0.1099	−0.1798
	(0.0023)	(0.0016)	(0.0021)
Normalized log TFPQ	0.9803	0.9713	0.9868
(Industry Elasticity)	(0.0006)	(0.0009)	(0.0008)
Observations	1463000	370000	1093000
R-squared	0.9658	0.9889	0.9820
Cluster Count	12896	4061	8835
Sigma	6	6	6
Industry Sample	ALL	OVERSTATED ELASTICITY	UNDERSTATED ELASTICITY
Industry-Year FE	YES	YES	YES

Panel B: Variable vs Constant Returns to Scale

	Normalized log TFPQ, CRTS		
	(1)	(2)	(3)
Normalized log Distortion	0.3770	0.3852	−0.1115
	(0.0020)	(0.0020)	(0.0099)
Normalized log TFPQ	0.6501	0.6544	1.0217
(Variable RTS)	0.0021	0.0020	0.0130
Observations	1456000	1370000	86000
R-squared	0.9780	0.9831	0.9548
Cluster Count	12679	11501	1178
Sigma	6	6	6
Industry Sample	ALL	OVERSTATED RTS	UNDERSTATED RTS
Industry-Year FE	YES	YES	YES

Note: An observation is an establishment-year. Clustered standard errors are in parenthesis. Errors are clustered at the industry-year level.

by equation (2.31). When returns to scale are overstated, as in column (2), so is productivity for more distorted establishments; the opposite pattern holds when returns to scale are understated in column (3).

Together, these two panels emphasize just how sensitive the correlation of productivity and distortion is to production-function parameters. In isolation, these correlations are not sufficient to inform us about the bias in measured misallocation; we breach that gap in the next section.

2.7 Measured Misallocation

Table 2.4 compares industry-level measures of misallocation across different models. We measure misallocation as the percent increase over industry TFP from equalizing distortions within the industry. The measure of bias compares these measures of misallocation across different model specifications. For instance, the first column of the table differences industry misallocation when the same production function is applied to all industries and the same measure when production functions vary across industries. Across all industry-years, the median increase in measured misallocation from misspecifying the constant RTS production function in 5%. There is substantial variation across industry-years, with an inter-quartile range from just below zero to a bit over 18%. Comparing the constant returns to scale model to one where returns to scale are potentially non-constant, the median bias is 33%, with an inter-quartile range of 17% to 58%.

Looking at expression (2.30), we can relate constant RTS misallocation bias to production-function parameters using two objects. The numerator suggests that

Table 2.4: Summary of Estimated Returns to Scale Coefficients

	Constant RTS Bias	Variable RTS Bias
25th Percentile	-0.0023	0.1674
50th Percentile	0.0539	0.3387
75th Percentile	0.1846	0.5796

the extent of the bias depends on the direction in which we mismeasure the labor elasticity, as well as the correlation of true productivity and the relative K/L ratio (henceforth ρ). In short, if we overstate the labor output elasticity, then we will overstate misallocation in industries where ρ is higher[3]. Table 2.5 captures these patterns. When α_{L_i} is overstated, then industry-years with a 1% higher correlation of relative K/L and productivity have a 0.3% larger mismeasurement of misallocation. Similarly, when α_{L_i} is understated, then industries with a 1% higher correlation of inverse K/L and productivity have a 0.5% larger mismeasurement of misallocation.

With this information in mind, we can now reinterpret Figure 2.1 through the lens of Tables 2.4 and 2.5. In short, in the U.S. manufacturing data, applying the same production function to all industries leads to a mismeasurement of the labor elasticity α_{L_i} that is systematically related to the correlation of productivity and distortions (as seen through variation in the K/L ratio). In industries where α_{L_i} is overstated, the correlation in question is generally high. This pattern leads to misallocation being overstated for most industries in most years. Consequently,

[3]To be consistent with equation (2.30), when we understate α_{L_i}, the exponent on the relative K/L ratio becomes negative. Hence, when we understate α_{L_i}, we calculate the correlation of productivity A_{ie} and the inverse of the relative K/L ratio, $\rho_{inverse}$. Misallocation should be increasing in $\rho_{inverse}$ when α_{L_i} is understated.

aggregate misallocation – an aggregate of sectoral misallocation measures – is systematically overstated, as in panel A of Figure 2.1.

Table 2.5: Measured Physical Productivity and Distortions

	Constant RTS Bias (1)	(2)
Correlation of Relative K/L and A	0.3015	
	(0.0137)	
Correlation of Inverse Relative K/L and A		0.4953
		(0.0178)
Observations	4000	9000
R-squared	0.1072	0.0966
Labor Output Elasticity	OVERSTATED	UNDERSTATED
Year FE	YES	YES

Note: An observation is an establishment-year. Clustered standard errors are in parenthesis. Errors are clustered at the industry-year level.

2.8 Conclusion

We highlight the challenge of separately identifying production function parameters and measures of distortions in a family of commonly used models for quantifying misallocation. Resolving this identification challenge is particularly important because mismeasured production-function parameters induce spurious correlations between productivity and distortions that bias measures of misallocation. We propose a way to identify this model in two steps. First, we show that we need only measure relative distortions to measure misallocation. By removing the absolute levels of distortions from the parameter space for identifying misallocation, we show that we need not identify the whole model to identify the measure of interest. Second, we emphasize that multiple specifications of the profit functions are consistent with these wedge-like distortions in establishment first order conditions. Given the data available to the econometrician, we highlight the one specification that can be implemented.

CHAPTER III

Multinational Corporations in the U.S.: A Profile of their U.S. Employment (with Vanessa Alviarez, Nicholas Bloom, Kyle Handley and Brian Lucking)[1]

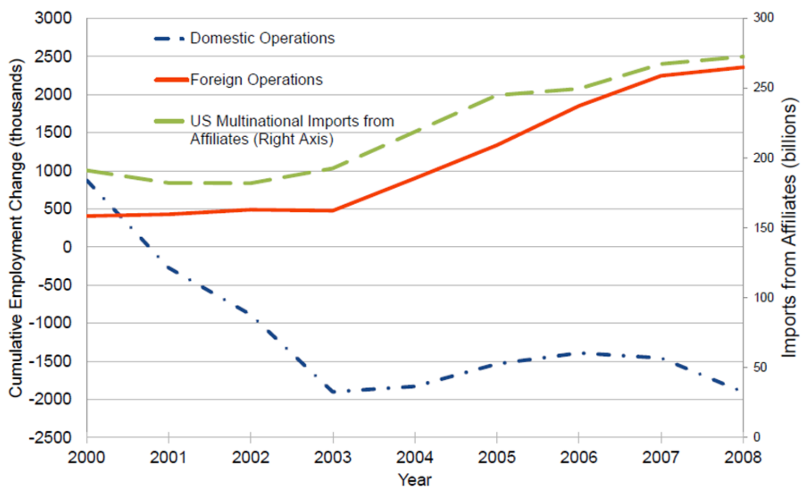
3.1 Introduction

Multinational corporations (MNCs) have a major impact on the global economy as they account for more than 50% of the world's GDP in recent years, as well as a significant portion of countries' employment and global trade. The employment and wage impact of U.S. MNCs' imports – offshoring – from low wage countries, such as China and Vietnam, has remained at the center-stage politically and economically. Rising global trade is likely to continue playing an important role in labor-market polarization and the decline of manufacturing activity.

[1]DISCLAIMER: "Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed." Bloom and Handley thank the Russell Sage Foundation and Handley thanks the W.E. Upjohn Institute for financial support.

Measuring the extent of multinational activity and its employment effects is difficult. For example, suppose General Electric (GE) closes down a light-bulb factory in Alabama. Those jobs may have been replaced by foreign workers, i.e. offshored, but maybe GE just decided to stop producing light-bulbs. Perhaps GE decided to outsource production to another U.S. producer, or perhaps it reduced domestic employment in manufacturing of light bulbs, but offset those jobs by increasing employment in design, engineering and wholesaling functions.

Figure 3.1: Cumulative employment change at domestically-owned and majority-owned foreign operations of non-bank U.S. multinationals (left axis) and imports from affiliates (right axis)



MNCs employed 28.6 million U.S. workers in 2011, accounting for 25% of the total U.S. wage income. Figure 3.1 plots the cumulative employment changes at the domestic and foreign operations of U.S. multinationals. During most of the 2000s, overseas employment at majority owned affiliates of U.S. multinationals was growing while domestic employment at multinationals was flat or falling rapidly. At the same time, imports from foreign owned affiliates were increasing. This is strongly suggestive of the type of employment offshoring that was alarming to policy makers. Increased import competition is both a cause and a consequence of increased offshoring. Greater low-wage import competition, especially from China, reduces wages and employment (Autor and Dorn, 2013; Pierce and Schott, 2016; Hummels et al., 2014). It also changes the nature of the employer-employee relationship and wage bargaining (Bertrand, 2004). Another line of research has investigated the employment and wage effects of offshoring, finding a range of effects depending on the time period, industry, or country groups (Feenstra and Hanson, 1996).

More importantly though, while the evidence in Figure 3.1 is suggestive, we cannot begin to measure and assess the role of multinational activities on employment growth and reallocation without a relevant comparison group. Returning to our light bulb example, perhaps employment declined at all firms in the lighting and small appliance industries, or at other large, legacy manufacturing operations, regardless of their global footprint. Many previous studies for the U.S. have been limited in this regard by the scope and availability of data. First, they rely on either the intensity of importing and exporting or the type of trade participation, arm's length vs. related party trade, to identify offshoring or the multinational status of firms. While these trade relationships are interesting in their own right, they may generate many false positives as a multinational identifier. For example, the threshold for related-party trade reporting, 6 percent or higher for imports and 10 percent for exports, are well below the measure for majority ownership or even levels that would confer sufficient control rights. Second, data sources that only survey or identify multinational firms cannot be used to compare multinationals to non-multinational firms that operate domestically or engage in importing and exporting at arm's length. These data sources may be used to identify differentials in employment among multinational firms, but are not well-suited for aggregate assessments of employment effects of multinationals. Third, most studies do not have longitudinal establishment level data within a multinational firm. This makes it very difficult, or impossible, to study employment reallocation within the firm. In particular, firms may shift employment substantially across units, open and close establishments, or grow through acquisitions and divestitures. These changes are not observed with firm and industry level data, and so the full scope and magnitude of employment reallocation and employment growth at MNCs relative to otherwise similar firms cannot be disentangled.

Our approach aims to measure the aggregate employment growth and reallocation effects of MNCs in the U.S. over the past decade and across manufacturing, retail, wholesale and service sectors. At a fundamental level, understanding the contribution of MNCs to U.S. employment growth in contrast to non-MNCs is the first-order issue. Do MNCs account disproportionately for the decline in U.S. manufacturing employment? Did they grow faster relative to their domestic counterparts? Did they create and destroy more jobs at new and existing establishments relative to controls? And, given that MNCs are often vertically integrated and operate multiple lines of business, in what sectors did they create and destroy jobs?

We answer these questions by exploiting a novel combination of two detailed firm level datasets: the restricted-use U.S. Census Bureau establishment-level microdata and the Bureau van Dijk Orbis database. The Orbis database has detailed information about ownership linkages between firms and across countries. The combined Census-Orbis dataset links firm and establishment-level activity to the scope and extent of a firm's global operations. To our knowledge, this is the first time these data have been linked and the detailed exploration as described above is unavailable elsewhere. By carefully matching the names and addresses between the firms in the Orbis database with the universe of U.S. firms in the confidential database at the U.S. Census, we can identify the U.S. firms and establishments that are part of a larger multinational operation; either being majority-owned U.S. affiliates of foreign multinationals firms or U.S. parent firms that have majority-owned operations overseas. In summary, the Census-Orbis dataset provides a more complete characterization of the operation of firms located in the U.S. and their linkages to operations overseas. Coupled with their trade transactions, we are able to further distinguish between intra-firm trade from arm's length trade.

This paper begins by analyzing the difference in overall employment growth rates between U.S. MNCs, foreign MNCs, exporters, importers and domestically-owned firms. Then, we analyze employment growth differentials of MNCs relative to controls for each component of net employment growth; i.e. job creation, including births and positive changes in employment at continuing establishments, and job destruction, including deaths and negative changes in employment at continuing establishments. We find that the overall employment growth rate varies substantially by firm-type, with MNCs having a positive and significant premium when compared with non-MNCs.

This paper is related to recent studies which look at the differential employment effects of MNCs, and the effects of offshoring by MNCs on domestic labor market outcomes. Autor et al. (2013) find that commuting zones that are more exposed to imports from China experienced larger reductions in manufacturing employment. Boehm et al. (2015) use firm ownership data from LexisNexis and similar Census micro data, and find that U.S. MNCs experienced larger declines in employment compared to similar domestically-owned manufacturers. Hummels et al. (2014), using matched employer-employee level data for manufacturing firms in Denmark, find that firms that increased imports experienced significant reductions in employment levels. An important distinction between these papers and ours is that they focused specifically on manufacturing employment. Yet, the vast majority of MNCs with operations in the manufacturing sector also operate in non-manufacturing sectors, such as retail, wholesale, information, professional services, administrative support, and management. By considering a firm's activities beyond the manufacturing sector, we take into account the substantial reorganization that could take place within the firm as it adjusts its employment level in manufacturing while expanding operations in services establishments (see Magyari (2016) for a recent study). Hijzen et al. (2011) analyze an extensive margin of multinationals' offshoring using data on French firms from 1987–1999. They find that when multinationals create new production affiliates abroad, the effects on domestic employment depend on the type of offshoring – the opening of new affiliates of manufacturing firms in high- (low-) income countries is associated with increases (no change) in domestic employment.

One of the main reasons MNCs might respond differently to a reduction in the cost of purchasing intermediates from abroad is that they can both adjust the extent of their local operations and reallocate production across their network of foreign affiliates within the corporate group. Therefore, the response of a multinational firm operating in the U.S. will depend on the extent of its operations across countries and sectors outside the U.S., relative to the activities performed locally.

Another reason why we could expect a differential employment effect by multinational firms is due to their ability to perform intra-firm trade transactions across borders. Multinationals' sourcing patterns are distinctive across goods, with some intermediate inputs being sourced from their own affiliates and others from unrelated parties (often in different countries)[2]. Moreover, it is possible that the local employment response to an increase in intra-firm imports differs from that of arm's length imports, because the goods produced within the same multinational firm can reduce the overall uncertainty relative to the stability of the shipments and the compliance with product specifications.

Several papers have analyzed the effects of MNCs using firm-level data on U.S. MNCs from the Bureau of Economic Analysis (BEA). Kovak et al. (2015) find that offshoring increases employment at U.S. MNCs, while Harrison and McMillan (2011) find that the effects of offshoring U.S. MNCs are heterogeneous, and depend on whether the tasks performed by foreign affiliates are likely to be more

[2]This is consistent with a feature of the Danish dataset highlighted in Hummels et al. (2014), who find that firms concentrate their imports purchases on a narrow set of goods that is largely unique to each firm.

or less similar to that performed by domestic workers. Desai et al. (2009) find that increases in investment and wages at foreign affiliates of U.S. MNCs are associated with increases in domestic investment and wages. A limitation of these analyses is that the BEA dataset only includes MNCs, so it is difficult to compare MNCs to similar domestically-owned firms using this data.

The rest of the paper is organized as follows. The next section discusses the main features of our dataset by providing details of the Orbis and U.S. Census datasets, respectively, followed by a section comparing our dataset with the public-use dataset on MNCs collected by the Bureau of Economic Analysis (BEA). Next, we describe the decomposition of employment growth rates and our empirical approach. We then present our baseline empirical evidence, establishing the role of MNCs in aggregate U.S. employment. Finally, we further decompose the role of MNCs in U.S. employment growth by looking at job creation and destruction measures, as well as establishment births and deaths.

3.2 Towards a New Comprehensive Database of Multinational Corporations in the U.S.

We combined the Bureau van Dijk Orbis worldwide database of firms (hereafter referred to as the Orbis database) with several restricted-use datasets at the U.S. Census to construct a matched Orbis-Census database that is suitable for the analysis of multinational corporations. This dataset would provide a more detailed and holistic picture of the operations of MNCs that operate in the U.S.

The Orbis database contains information such as contact details, industry affiliation and financial data, for both public listed and non-listed firms. The most striking feature of this database is the detailed ownership information of direct and indirect shareholders as well as subsidiaries for each firm.

Meanwhile, the restricted-use datasets at the U.S. Census, i.e. the Longitudinal Business Dataset (LBD) and the Longitudinal Foreign Trade Transaction Database (LFTTD), contain a wide range of establishment and firm-level information of the universe of firms operating in the U.S., including their employment information (number of employees and payroll) and international trade transactions at the finest level of product disaggregation.

By combining these datasets in a unified framework, we offer a unique portrait of the activity carried out by MNCs. First, we are able to identify the multinational status of firms located in the U.S., distinguishing between U.S. MNCs based in the U.S.; affiliates of foreign corporations operating in the U.S.; and domestically-owned (non-MNCs) firms. Second, through the ownership linkages in Orbis, we can track the operations of the network of U.S. foreign affiliates abroad, as well as the overseas operations of affiliates of foreign parents, including their activities in the source country. Finally, it allows for the construction of an alternative measure of intra-firm trade by tracking trade transactions between foreign exporters and U.S. importers within the same corporation. Hence, the Orbis-Census dataset allows us to identify both counterparts of each international trade transaction for U.S. imports.

This combined dataset will overcome some of the limitations of past studies on

MNCs. There are three datasets that have often been used to study MNCs: Orbis, LFTTD, and the multinational database at the Bureau of Economic Analysis (BEA). Despite the richness of each of these datasets individually, they have important shortcomings that can be overcome by combining them in a unified framework. First, the main advantage of Orbis is the scope and accuracy of firms' ownership information. But, it lacks information on the exporting and importing activities carried out by these firms.[3] Second, the LFTTD contains detailed information of U.S. firms' international trade transactions. Furthermore, it specifies whether each trade transaction is carried out with a related or unrelated party in a foreign market. For importers, in particular, the LFTTD provides an identifier for the foreign exporter. It does not, however, have information on the degree of ownership or any financial information about these foreign firms. Finally, the BEA dataset contains information of production, employment and trade for U.S. MNCs and affiliates of foreign MNCs operating in the U.S., but it does not contain detailed exports and imports information (e.g. trade by country and/or by product). Another downside of this dataset is that it only covers MNCs, making it impossible to compare the performance of multinationals relative to exporters that are non-MNCs and purely domestically-owned (non-MNC) firms.

3.2.1 Identifying Multinationals in Orbis

In this section, we describe how MNCs with operations in the U.S. are identified from the Orbis dataset. From the firm-level ownership information, we are able to

[3] Moreover, due to confidential agreements of Bureau van Dijk's information provider in the U.S., Orbis does not contain the complete annual financial information for firms located in the U.S.

build a network of firms that are related through ownership linkages. Then, we can identify each corporation's country of origin and its international coverage (the number of firms and countries of operation). One possible method that could be undertaken to achieve this is to identify the parent company of the corporation. Then, all firms that are properly identified to be owned by this parent company will be members of the corporation.

There are two challenges in accurately identifying a parent company in the Orbis dataset. First, if taken purely at face value, the different levels of ownership information provided by Orbis may lead researchers to draw the wrong conclusion of the true ownership structure of a corporation. For each firm, Orbis provides three different levels of ownership that can be used to identify the parent company for a given firm. They are: (1) the global ultimate owner (GUO), which exercises the greatest degree of control over the firm and is not itself controlled by any other company; (2) the domestic ultimate owner (DUO), which is the highest company in the ownership pyramid located in the same country as the firm; and (3) the immediate shareholder (ISH), which is the largest direct shareholder of the firm and may or may not be located in the same country.

All three ownership measures are useful, but no one alone can accurately identify the extent of a corporation that would be meaningful for our analysis. The immediate shareholder (ISH) of a firm, which is its largest direct owner, could lead us to believe that a company is domestically owned when it is actually foreign owned. For instance, according to Orbis, Samsung Semiconductor Europe Limited in the U.K. is directly owned by Samsung Electronics Co, a company also located in the U.K. Nonetheless the global ultimate owner of both firms is Samsung Electronics Co., Ltd located in Korea. In fact, we show in the appendix that using the ISH alone will lead to 20 percent of foreign affiliates in a given country being misclassified as domestically-owned, even when, in reality, they are part of a global network. Furthermore, by using the ISH alone, one may correctly conclude that a firm is foreign-owned but incorrectly identify the country of origin. For instance, based on the ISH, Volkswagen France will be classified as foreign-owned with its country of origin being Italy, since it is directly owned by Volkswagen Italy. In reality, its global ultimate owner is in Germany. We find that if researchers were to use the ISH alone to identify ownerships, about 15 percent of foreign firms will be correctly classified as foreign-owned but attributed to a wrong country of origin. Some of these problems can be overcome by using the GUO instead. But, as we shall describe next, the GUO indicator also has important drawbacks.

The second challenge in correctly identifying a parent company is that the dataset defines ownership in terms of financial shareholding, which does not necessarily correspond to the notion of management control implied in most economic models of trade and multinational production. These models define a multinational corporation as an entity that performs innovation and production activities in different countries through its network of affiliates whose operations are managed by a common parent firm. In most models, the parent firm is an entity that makes strategic decisions for the corporation, such as the location of its affiliates, choices and levels of production, and other strategic issues. For example, through the lens of the model, we would expect all of Ford's affiliates that design, assemble and produce in other countries to be owned by Ford Motors Co. which is located in the U.S., the home country of the headquarter of the corporation. Similarly, worldwide affiliates belonging to the Toyota corporation should have Toyota Co., which is located in Japan, as their parent company. The extent to which the ownership structure obtained from Orbis can provide this picture of global ownership of firms is one key reason why this data source can be a useful resource in our study of MNCs.

Ownership structures are often complex, however, and there are several situations in which the parent company defined in terms of the highest financial shareholder may not be the same as the the actual management parent. It is not unusual for MNCs to create holding companies to manage their assets, patents, trade marks, etc. For tax purposes, these are located in a country different to the source country where the management body or the company resides. For example, Cisco System Italy S.R.L. is categorized to be ultimately owned by Cisco ISH B.V, a holding company located in the Netherlands. In reality, it is part of a U.S. multinational corporation. Furthermore, some firms are majority owned by financial institutions such as banks, insurance companies or mutual funds[4].

Therefore, we propose combining the best features of the GUO and ISH identifiers to determine the boundaries of corporations and their countries of origin. Under this proposed method, the identity of the parent company per se is not what matters the most. Instead, we introduce the concept of a corporate group in addressing these challenges. A corporate group refers to a conglomerate of compa-

[4]For example Citibank, BNP Paribas and Deloitte are categorized by Orbis to be global ultimate owners and immediate shareholders of many industrial companies.

nies related by ownership ties, sharing a common parent that exerts management control over the group. First, to avoid creating spurious corporate groups in which the GUOs are financial institutions, we restrict our dataset to only GUOs that are industrial firms. Second, we group all firms that share a common GUO, DUO and ISH to be in the same corporate group. Third, we assign the country of origin of each corporate group in the following way. In cases in which the country of origin of the GUO is the same as that of the ISH, then we will designate that to be the country of origin for all firms in the corporate group[5]. In other cases, we rely on other financial indicators to help determine the country of origin of the corporate group. For this, we calculate the total assets, revenue, employment and the number of affiliates of the corporation in each country in which it has operations. Finally, we conduct an exhaustive examination through visual inspection in order to correct for any discernible errors. Specifically, we manually inspected firms in the upper tail of the size-sector distribution and also corporate groups for which we have not been able to fully employ the above steps.

3.2.2 U.S. Census Data

We employ three restricted-use firm and establishment level datasets at the U.S. Census for this paper. First, we matched our Orbis dataset with the Business Register (Standard Statistical Establishment List (SSEL)) to create a bridge file. Amongst others, the Business Register contains the names and addresses of business entities

[5]Whenever the country of origin is a tax haven economy, we will investigate manually by searching the history of the firms within the corporate group and make manual adjustments whenever necessary.

with paid employees in the U.S. (Jarmin and Miranda, 2002). The name and address information on the Business Register are used as our primary inputs for matching the Orbis dataset to the other micro datasets at the U.S. Census. Further details on the matching procedure are discussed below.

For the entities that are matched, we obtained their firm and establishment identifiers from the Business Register and used these identifiers to merge to the Longitudinal Business Database (LBD) and the Longitudinal Firm Trade Transactions Database (LFTTD). In the LBD, we excluded establishments that are out-of-scope for County Business Patterns. For the remaining in-scope establishments, we obtained the number of employees for each establishment as well as the establishment's industry code at the NAICS 6-digit level[6]. For analysis at the firm-level, we summed the total number of employees for all establishments that share the same firm identifier and defined the aggregated value to be the number of employees of that given firm. For multi-unit firms, we undertook an intermediate step whereby we summed the number of employees for all establishments that share the same NAICS 3-digit industry code. We defined the firm's industry sector to be the NAICS 3-digit industry in which the firm has the highest number of employees.

The LFTTD is a firm-level dataset of the universe of imports and exports trade transactions data collected by the Customs Bureau. Amongst others, the dataset contains variables such as the value of the transaction, product code (Harmonized System) and the country of origin or destination. Hence, in addition to our multinational identifier, we are also able to identify MNCs that import and/or export

[6]That is, the most recent census year NAICS code reported for the establishment. Census years refer to years ending in "2" or "7" (i.e. 1982, 1997).

from merging our baseline dataset with the LFTTD.

3.2.3 Matching Orbis with the Business Register at the U.S. Census

We match the names and addresses of firms that we have identified to be multinationals from the Orbis dataset to the Business Register's names and addresses records[7]. For any given year of Orbis firms, we first matched these firms to the Business Register for that given year. We recognize that the timing of these two datasets may differ (for example, due to different fiscal years and financial statements dates in Orbis). As such, for Orbis firms that are unmatched, we would also search for them in adjacent years in the Business Register.

We start our matching procedure with a conservative exact match on names and addresses (i.e. street address and zipcode). For Orbis firms that remain unmatched, we next employed a fuzzy matching algorithm. This algorithm works by constructing a match code for the combination of a firm's name and address, by taking into consideration possible variations in the spelling of a firm's name and street address. A more detailed explanation of our procedure is provided in Appendix C.1.

Matching based on names and addresses presented us with several challenges. First, we encountered cases of non-unique (none one-to-one) matches. A "firm" in Orbis could be matched to multiple firms in the Business Register in a given year. This situation could arise due to the different definition of a "firm" used in

[7]Our filtering procedure of the Orbis dataset allows for us to also identify purely domestically-owned firms that have ownership linkages but only within the U.S. We also included these firms in our matching procedure for completeness.

the construction of the two datasets. Given that our goal is to identify MNCs in the Business Register, we would then designate that all of the multiple matches in the Business Register be MNCs if the Orbis firm that is matched is a multinational. In other words, the characteristic of the Orbis firm would be "passed on" to the matched Business Register firms. On the other hand, the opposite case of multiple Orbis firms being matched to one Business Register firm could also arise. In most instances, the multiple Orbis firms that are matched would belong to a single corporate group. Here, our definition of a corporate group helps to resolve this issue. Since a corporate group would have a unique identification of its multinational status (and its country of origin), we would assign the characteristics of the corporate group directly to the matched firm in the Business Register.

After this round of matching, we would then verify that our matches are sensible. First, we combined the firms that we have matched with the LFTTD and calculated the aggregate value of trade (imports and exports) for MNCs and non-MNCs. Based on earlier studies, we know that a significant proportion of the U.S.' international trade transactions is carried out by MNCs. We find similar results in our analysis.

Upon matching and verifying that the matches are valid, we obtain the establishments associated with the firms that are matched from the LBD. Tracking establishments is important in our analysis as we are interested in examining how MNCs create and destroy jobs across the various margins of births/deaths of establishments, at continuing establishments, and through acquisitions and divestitures.

3.3 External Validity of the Matched Dataset

In this section, we provide some descriptive statistics pertaining to the pattern of employment and trade of MNCs in the U.S., and compare that with the public-used data provided by the Bureau of Economic Analysis (BEA).

Table 3.1 compares the employment levels of U.S. parents and U.S. affiliates of foreign parents as calculated in our matched dataset, with the employment levels reported by the BEA. Specifically, this table reports the employment statistics for two Census years (2007 and 2012) and for four broad industries. From the upper panel of Table 3.1, we note that the total employment for U.S. multinationals and foreign-owned multinationals in 2012 closely matched the corresponding values as measured by the BEA. Specifically, our matched dataset reports a marginally lower total number of employees of U.S. parents in the U.S. (lower by 3.1%) but closely matched the total number of employees of foreign affiliates in the U.S. (lower by 0.1%). Nevertheless, there are discrepancies in the industrial employment composition in both datasets. In particular, the matched dataset captures 77% of the manufacturing employment by foreign affiliates in the U.S. and around half of the manufacturing employment (51.6%) of U.S. parents, relative to the BEA values. For the other sectors, the matched dataset overestimates the number of employees in wholesale, retail and services sectors by 12.5% (12%), 27.1% (19.3%), and 12.5% (12.5%), for U.S. parent and foreign affiliates in the U.S, respectively.

There are two possible reasons for these discrepancies. First, in Table 3.1, employment has been aggregated based on the industry of the establishment, rather than based on the industry of the firm, which can be assigned on an employment-weighted basis for multi-unit firms. Second, in terms of the differences in total employment in 2012, the publicly available BEA dataset reports the employment level of all U.S. parents and U.S. affiliates of foreign parents (which include parents and affiliates of both banks and non-banks) while we have explicitly omitted financial institutions from our Orbis dataset.

3.4 Decomposing Employment Growth

In this paper, we wish to examine how MNCs contribute towards aggregate employment changes in the U.S. economy over time. To do so, we consider how employment changes reflect the contributions of continuing establishments within a firm, births of new establishments, and deaths of existing establishments.

As is now standard in the study of business dynamics, the following definitions are used in the decomposition of net job creation into the different margins as discussed in the main text. First, at the establishment level, job creation (JC) and job destruction (JD) are defined as:

$$JC_{et} = \max(g_{et}, 0) \text{ , and}$$
$$JD_{et} = \max(-g_{et}, 0) \text{ .}$$

For establishments that newly enter in period t, the job creation rate would be $+2$, while for establishments that exit in period t, the job destruction rate would be -2.

To aggregate up to the firm level, we obtain the following expressions for the job creation and destruction at firm i.

$$JC_{it} = \sum_{e} \frac{X_{et}}{X_{it}} \max(g_{et}, 0) \tag{3.1}$$

$$JD_{it} = \sum_{e} \frac{X_{et}}{X_{it}} \max(-g_{et}, 0) \tag{3.2}$$

Net job creation ($NetJC_{it}$) within the firm is defined as the difference between the number of gross job gains (JC_{it}) and the number of gross job losses (JD_{it}) within the firm.

$$NetJC_{it} = JC_{it} - JD_{it}$$

Using establishments details, we decomposed gross job gains into the contribution from births, acquisitions and expanding establishments.

$$JC_{it} = JC_{it}^{cont} + JC_{it}^{birth} + JC_{it}^{acquisition}$$

Likewise, gross job losses is the sum of deaths, divestitures and contracting establishments.

$$JD_{it} = JD_{it}^{cont} + JD_{it}^{death} + JD_{it}^{divestiture}$$

We employ the mid-point growth measure by normalizing the gross job flows by the mean of total employment between periods t and $t-1$ to obtain

$$\Delta emp_{i,t} = \frac{JC_{it} - JD_{it}}{0.5\left(emp_{i,t} + emp_{i,t-1}\right)} \in [-2, 2] \ .$$

Therefore, the contribution of JC_{it} and JD_{it} to the employment growth rate is:

$$\begin{aligned}
\Delta emp_{i,t}^{JC} =& \frac{JC_{it}}{0.5\left(emp_{i,t} + emp_{i,t-1}\right)} \in [0, 2] \text{ , and} \\
\Delta emp_{i,t}^{JD} =& \frac{JD_{it}}{0.5\left(emp_{i,t} + emp_{i,t-1}\right)} \in [-2, 0] \ .
\end{aligned}$$

As discussed in previous studies on job dynamism in the U.S. (e.g. Haltiwanger et al. (2013)), high churning rates during healthy economic times have contributed towards productivity growth of the U.S. economy. Specifically, in the context of this study on MNCs, we are interested in examining if the churning rate of MNCs is substantially different from that of non-MNCs.

$$\text{Churning}_{it} = JC_{it} + JD_{it}$$

We also measure the excess reallocation rate of firms following the definition given in Davis et al. (1996). This measures the total amount of churn that is over and above that which is due to net changes in employment.

$$\text{Excess Reallocation}_{it} = JC_{it} + JD_{it} - |JC_{it} - JD_{it}|$$

3.5 Empirical Approach

The main contribution of this paper is that we introduce multinational indicators in our analysis of business dynamics of U.S. firms. We use a nonparametric regression approach to estimate these relationships (see Haltiwanger et al. (2012) and Haltiwanger et al. (2013) for similar approaches conducted in different settings). Our first set of regressions would be to compare the employment outcomes for MNCs with non-MNCs.

$$\Delta emp^{j}_{i,t,t-1} = \beta_0 + \beta_1 MNC^{All}_i + \nu_{i,t} + \epsilon_{i,t} \ , \tag{3.3}$$

where MNC^{All}_i is a binary indicator; 1 for firms that we have identified through our matches to the Orbis dataset as a multinational (regardless of ownership status[8]) and 0 otherwise[9]. $\nu_{i,t}$ is the size $\times$ age $\times$ industry $\times$ multi-unit status fixed effects. The main dependent variable is the annual net job flow at the firm level. Later, we will describe the various decompositions that we conducted to measure their contributions towards the firm's total net job flow. Next, we split the MNC^{All} group into *US-owned MNC* and *foreign-owned MNC*. We then ran the following regression.

$$\Delta emp^{j}_{i,t,t-1} = \beta_0 + \beta_1 MNC^{US}_i + \beta_2 MNC^{F}_i + \nu_{i,t} + \epsilon_{i,t} \ , \tag{3.4}$$

[8]This indicator includes both U.S.-owned multinationals and U.S. affiliates of foreign-owned multinationals.

[9]The omitted group includes all US-firms in the LBD that we did not match to the ORBIS MNC indicators and also ORBIS firms that we matched but were identified to be purely domestic.

where MNC_i^{US} is a binary indicator with 1 for firms that we have identified through our matches to be *US-owned MNC* and 0 otherwise; and MNC_i^F is a binary indicator with 1 for firms that we have identified through our matches to be *Foreign-owned MNC* and 0 otherwise. The omitted group in this regression is similar to that in equation (3.3).

Our third set of regressions involves further splitting the non-MNC firms into four sub-groups; firms that engaged in exporting only, firms that engaged in importing only, and firms that engaged in both exporting and importing activities.

$$\Delta emp_{i,t,t-1}^j = \beta_0 + \beta_1 MNC_i^{US} + \beta_2 MNC_i^F + \beta_3 Exp_i + \beta_4 Imp_i + \beta_5 Both_i + \nu_{i,t} + \epsilon_{i,t} \tag{3.5}$$

where Imp_i is a binary indicator with 1 for firms that engaged in importing only, 0 otherwise; Exp_i is 1 for firms that engaged in exporting only, 0 otherwise, and $Both_i$ is 1 for firms that engaged in both importing and exporting activities, 0 otherwise. Therefore, the omitted group in this specification would be non-MNC firms that do not engage in any international trade activity.

In terms of the decomposition of firm's employment outcomes, we first decomposed the firm's total annual net job flows across the following margins: job creation of continuing establishments, births and acquisitions; and job destruction at continuing establishments, deaths and divestitures.

We also examined the decomposition of firm's employment outcomes by the sectoral composition of the firm's establishments. Consider a multi-unit firm which owns establishments in the manufacturing sector (NAICS 31, 32 or 33) and also in the wholesale trade sector (NAICS 42). By aggregating the total employment of the firm up to the firm-sector level, we can then decompose the firm's annual net job flows into the contribution attributed to each of these sectors.

$$\Delta emp_{i,t} = \Delta emp_{i,t}^{Manufacturing} + \Delta emp_{i,t}^{Wholesale} + \Delta emp_{i,t}^{Retail} + \Delta emp_{i,t}^{Services}$$

We will then repeat the decomposition for all the other margins (job creation at continuers, births, etc.) along the firm-sector dimension. The above regressions are estimated two ways: unweighted and weighted. The weights used in the weighted regressions are constructed by weighting the changes in the firm's employment outcomes by the firm's average employment between period $t-1$ and t.

Next, we examine the role of international trade on the employment outcomes of MNCs. As a baseline measure of related-party trade, we first used the indicators provided in the LFTTD[10]. We estimated the following regression.

$$\begin{aligned}\Delta emp_{i,t,t-1}^{j} =& \beta_0 + \beta_1 MNC_i^{US} + \beta_2 MNC_i^{F} + \beta_3 RP_{i,t}^{imp} + \beta_4 nonRP_{i,t}^{imp} + \beta_5 RP_{i,t}^{exp} + \\ & \beta_6 nonRP_{i,t}^{exp} + \beta_7 MNC_i^{US} \times RP_{i,t}^{imp} + \beta_8 MNC_i^{US} \times nonRP_{i,t}^{imp} + \\ & \beta_9 MNC_i^{F} \times RP_{i,t}^{imp} + \beta_{10} MNC_i^{F} \times nonRP_{i,t}^{imp} + \beta_{11} MNC_i^{US} \times RP_{i,t}^{exp} + \\ & \beta_{12} MNC_i^{US} \times nonRP_{i,t}^{exp} + \beta_{13} MNC_i^{F} \times RP_{i,t}^{exp} + \beta_{14} MNC_i^{F} \times nonRP_{i,t}^{exp} + \\ & \nu_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3.6}$$

with $RP_{i,t}^{k}$ being defined as either a binary indicator (1 for firm i that engaged

[10]In future work, we intend to develop our own measures of related-party indicators based on the variables in our matched dataset.

in any related party import or export transactions in year t, 0 otherwise and k indicating imports or exports) or a continuous variable (natural log of the value of related party imports or exports in year t).

3.6 Empirical Evidence

3.6.1 Higher total employment growth rates for MNCs relative to non-MNCs

Table 3.9 reports the weighted regression results for our baseline regression specification. In Column (1), we find that with year fixed effects only, the employment growth rate for MNCs is not significantly different when compared with non-MNCs. However, with a fully-saturated regression model, the sign of the coefficient on the MNC indicator is positive and significant. The average annual employment growth rate for MNCs is 5.1 percentage points higher than that for non-MNCs. This result suggests that a simple comparison of the mean growth rates between MNCs and non-MNCs would indicate that there is no significant difference in the two groups' employment growth rate. However, once we compare these MNC firms with a suitably defined control group; that is, non-MNC firms with similar characteristics (age, size, industry, multi-unit status), we find that MNCs register higher employment growth rates.

When we analyze the differences between the different types of multinationals; i.e. between the U.S.-owned MNCs and the U.S. affiliates of foreign-owned MNCs, we find that the coefficients on the U.S. MNC and foreign MNC indicators are broadly similar (see Column (4)). This suggests that there is no significant difference in the employment growth rates between U.S.-owned and foreign-owned MNCs.

Upon decomposing the total net employment growth rates between gross job creation and gross job destruction, we find that MNCs create more and destroy fewer jobs than non-MNCs. MNCs' job creation rate is 4.2 percentage points higher than non-MNCs (Table 3.10) while their job destruction rate is 0.9 percentage points lower than non-MNCs (Table 3.11). The birth and acquisition of establishments account for most of the MNCs' job creation premium. Meanwhile, the destruction of fewer jobs by continuing establishments accounts for most of the MNCs' lower job destruction rate.

Given that MNCs recorded higher rates of hiring and firing relative to non-MNCs, this is reflected in the higher job churning rate of MNCs (+3.3 percentage points) as shown in Panel A of Table 3.12). In addition, the excess reallocation rate of MNCs is also higher (+2.4 percentage points).

3.6.2 MNCs are creating relatively more jobs across all sectors - notably, in the services sector

One of the goals of this study is to measure the sectoral contribution of the employment outcomes of MNCs. Towards this end, Table 3.13 shows the results of firm-sector decomposition of net employment growth by the broad sectors of manufacturing, wholesale trade, retail trade and services. For a single-unit firm, the sector of the firm is given in the LBD[11]. For a multi-unit firm, we aggregated up

[11]The industry codes of the establishments are recorded in the LBD at the NAICS 6 digit level. We consider a sector to be at the NAICS 1-digit level.

the employment of its establishments according to their sectors.

We find that the employment growth rates of MNCs are higher than those of non-MNCs across all sectors. Although total employment in the manufacturing sector has been declining in the U.S. over time (see Table 3.3), we find that the decline has not been more severe in MNCs in the time period that we are examining. On the contrary, the employment growth of MNCs in the manufacturing sector is 1 percentage point higher than non-MNCs. Moreoever, we find that the employment growth premium of MNCs is significantly higher in the services sector (+3 percentage points). On average, the services sector contributes 60 percent of the total employment growth premium of MNCs. Looking more specifically at the sectoral contribution for the different ownership structures of MNCs, we find that the sectoral contribution of the services sector is the largest for both U.S.-owned MNCS as well as for U.S. affiliates of foreign MNCs, relative to that of non-MNCs (Table 3.14).

3.6.3 U.S.-owned MNCs that also import exhibit lower employment growth rates

Table 3.6 and Table 3.7 describe two features of the international trade activities of MNCs in the U.S. First, we note that on average, U.S.-owned MNCs both import from and export to a higher number of countries relative to affiliates of foreign-owned MNCs as well as other non-MNC importers. Second, MNCs (both U.S. and foreign owned) imported a significantly higher number of products (measured at the HS-10 level) compared to other non-MNC importers. Furthermore, U.S.-owned

MNCs also exported significantly higher number of products relative to foreign-owned MNCs and other non-MNC exporters. This finding is consistent with the results from past studies that found that the bulk of international trade transactions in the U.S. has been conducted by MNCs.

In terms of related party trade values, Table 3.8 shows that more than two-thirds of the total imports of foreign-owned MNCs have been recorded as related-party transactions. While still high, the share for U.S.-owned MNCs is lower, at slightly less than half. This finding is also consistent with the view that MNCs have globally integrated production chains; such that they are active in both sourcing and selling their products and inputs between affiliates across national boundaries[12].

Table 3.15 reports the relationship between importing, exporting and multinational status on firms' employment growth rates. In this table, the related party indicators are binary (i.e. defined to be equal to one as long as the firm recorded any value of related-party imports or exports). In column (1), we find that when we look at firm employment across all sectors, on average, for U.S.-owned MNCs that imported on a non-related party trade basis, the marginal effect of non-related party import is negative on the firm's employment growth. A similar pattern of negative marginal effect is observed across all major sectors (see Columns (2) to (5)). In terms of related-party trade, we do not observe a negative marginal effect for overall firm employment for all sectors[13]. Table 3.16 presents the related party and

[12]Table 3.8 also shows positive shares for non-MNCs. Such cases arise because of the low percentage share of ownership that is used to define a related-party transaction in the LFTTD.

[13]Sectorally, only the Wholesale Trade sector shows a small negative marginal effect.

non related party trade variables in terms of the natural logarithms of their values. The signs and significance levels of the marginal effects of non-related party log imports for U.S.-owned MNCs are similar to that presented in Table 3.15. For all sectors, on average, a one percent increase in non-related party import is associated with a 0.4 percentage point decline in annual employment growth rates.

In subsequent work, we intend to directly estimate the effect of changes in imports at the firm level on employment growth and reallocation measures. Because of the obvious simultaneity problem that import levels and growth may be correlated with demand and supply shocks at the firm, we propose to use an instrumental variables strategy to address this endogeneity problem.

3.7 Conclusion

This paper measures the aggregate employment growth and reallocation effects of multinational firms in the U.S. over the past decade and across the manufacturing, retail, wholesale, and service sectors. We constructed a comprehensive and detailed firm and establishment-level database that allows us to properly identify both U.S.-owned MNCs and affiliates of foreign MNCs in the U.S.. Moreover, our dataset also consists of non-MNCs thereby providing us with a suitable control group for this study. Using our newly constructed dataset, we compared the contribution of MNCs to U.S. employment growth in contrast to non-MNCs.

We find that MNCs recorded higher total employment growth rates relative to the comparison group of non-MNCs. In particular, we find that MNCs create more and destroy fewer jobs than non-MNCs. Moreover, MNCs are found to have created relatively more jobs across all sectors; notably in the services sector. This result suggests that within-firm reallocation across sectors may be increasingly important in the study of business dynamism.

We do find that U.S.-owned MNCs that also engaged in importing activities exhibit lower employment growth rates. This negative marginal effect is observed across all major sectors. In subsequent work, we intend to directly estimate the effect of changes in imports at the firm level on employment growth and reallocation measures using an instrumental variables strategy to address the endogeneity problem.

Table 3.1: U.S. Census-Orbis and BEA Comparison (Employment Count, '000)

	US Census−Orbis		BEA	
	US MNCs	Foreign MNCs	US MNCs	Foreign MNCs
		Year = 2012		
Manufacturing	3,544	1,702	6,873	2,200
Wholesale	1,239	628	1,102	561
Retail	5,447	629	4,286	527
Services	11,916	2,875	10,595	2,555
Total	22,146	5,834	22,855	5,843
		Year = 2007		
Manufacturing	4,337	1,963	7,217	2,051
Wholesale	1,370	658	1,065	662
Retail	5,534	603	4,001	530
Services	12,328	3,078	10,151	2,307
Total	23,569	6,302	22,433	5,550

[a] Sectors are defined at the establishment level.
[b] In the BEA data, activity of U.S. MNCs corresponds to the activity of all US parents, and it is classified under the industry of the parent.
[c] In the BEA data, activity of foreign affiliates in the U.S. corresponds to majority-owned bank and nonbank U.S. affiliates, and it is classified under the industry of the affiliate.

Table 3.2: Establishments Count and Growth Rates

	Non MNC Exporter & Importer	Non MNC Exporter Only	Non MNC Importer Only	Non MNC Non trader	**Non-MNC TOTAL**	US MNC TOTAL	Foreign MNC TOTAL	**MNC TOTAL**
Panel A: Establishment Count ('000)								
				Year = 2012				
Manufacturing	44	27	20	155	246	17	11	28
Wholesale	74	28	49	169	320	31	21	52
Retail	96	23	75	587	781	158	37	195
Services	135	73	124	3,492	3,824	276	57	333
NEC	3.2	0.5	1.4	4.9	10	8.2	2.6	11
TOTAL	**352**	**152**	**269**	**4,408**	**5,181**	**490**	**129**	**619**
				Year = 2007				
Manufacturing	44	27	23	181	275	19	12	31
Wholesale	71	27	55	189	342	30	22	52
Retail	86	27	86	626	825	155	36	191
Services	138	68	110	3467	3,783	276	64	340
NEC	3.3	0.5	1.5	6.2	11.5	7.3	2.7	10
TOTAL	**342**	**150**	**276**	**4,469**	**5,237**	**487**	**137**	**624**
Panel B: Average Annual Growth Rates (2008-2012)								
Manufacturing	0.2%	-0.4%	-3.2%	-3.1%		-2.6%	-1.5%	
Wholesale	0.9%	0.7%	-2.5%	-2.2%		0.3%	-0.8%	
Retail	2.1%	-3.2%	-2.7%	-1.3%		0.3%	0.4%	
Services	-0.5%	1.5%	2.4%	0.1%		0.0%	-2.3%	
NEC	-0.9%	0.5%	-2.1%	-4.2%		2.2%	-0.4%	
Panel C: Growth Rates between 2007-2012								
Manufacturing	1.2%	-2.0%	-15.9%	-15.5%	-11.1%	-12.7%	-7.3%	-10.2%
Wholesale	4.7%	3.7%	-12.5%	-11.1%	-6.6%	1.4%	-4.0%	0.0%
Retail	10.6%	-16.0%	-13.5%	-6.5%	-5.5%	1.4%	1.8%	2.1%
Services	-2.6%	7.4%	11.8%	0.7%	1.1%	0.1%	-11.3%	-2.1%
NEC	-4.6%	2.5%	-10.5%	-21.9%	-14.0%	11.2%	-2.0%	7.7%

[a] Sectors are defined at the establishment level.

Table 3.3: Employment Count and Growth Rates

	Non MNC				**Non-MNC**	US MNC	Foreign MNC	**MNC**
	Exporter & Importer	Exporter Only	Importer Only	Non trader	**TOTAL**	TOTAL	TOTAL	**TOTAL**
Panel A: Establishment Count ('000)								
					Year = 2012			
Manufacturing	3,141	653	567	1,459	5,820	3,544	1,702	5,246
Wholesale	1,570	286	657	1,161	3,674	1,239	628	1,867
Retail	2,522	412	1,230	4,449	8,613	5,447	629	6,076
Services	7,384	1,818	7,255	41,448	57,905	11367	2760	14127
NEC	164	12	45	34	255	549	115	664
TOTAL	**14,781**	**3,181**	**9,754**	**48,551**	**76,267**	**22,146**	**5,834**	**27,980**
					Year = 2007			
Manufacturing	3,382	745	782	1,926	6,835	4,337	1,963	6,300
Wholesale	1,529	293	798	1,376	3,996	1,370	658	2,028
Retail	2,232	476	1,602	4,973	9,283	5,534	603	6,137
Services	7,019	1,622	6,820	40,921	56,382	11,778	2,954	14,732
NEC	161	14	60	43	278	550	124	674
TOTAL	**14,323**	**3,150**	**10,062**	**49,239**	**76,774**	**23,569**	**6,302**	**29,871**
Panel B: Average Annual Growth Rates (2008-2012)								
Manufacturing	0.2%	-0.4%	-3.2%	-3.1%		-2.6%	-1.5%	
Wholesale	0.9%	0.7%	-2.5%	-2.2%		0.3%	-0.8%	
Retail	2.1%	-3.2%	-2.7%	-1.3%		0.3%	0.4%	
Services	-0.5%	1.5%	2.4%	0.1%		0.0%	-2.3%	
NEC	-0.9%	0.5%	-2.1%	-4.2%		2.2%	-0.4%	
Panel C: Growth Rates between 2007-2012								
Manufacturing	-7.4%	-13.1%	-31.9%	-27.6%	-16.0%	-20.1%	-14.3%	-18.3%
Wholesale	2.6%	-2.3%	-19.3%	-16.9%	-8.4%	-10.0%	-4.7%	-8.3%
Retail	12.2%	-14.2%	-26.3%	-11.1%	-7.5%	-1.6%	4.2%	-1.0%
Services	5.1%	11.4%	6.2%	1.3%	2.7%	-3.6%	-6.8%	-4.2%
NEC	1.9%	-15.4%	-28.0%	-23.4%	-8.6%	0.0%	-7.7%	-1.5%

[a] Sectors are defined at the establishment level.

Table 3.4: Firm Count and Growth Rates

	Non MNC				US MNC	Foreign MNC
	Exporter & Importer	Exporter only	Importer only	Non trader	TOTAL	TOTAL
Panel A: Firm Count ('000)						
Year = 2012						
Manufacturing	33	25	18	152	2.2	2.9
Wholesale	44	25	39	158	1	3.7
Retail	9	15	34	519	0.5	0.4
Services	13	29	41	3092	4.1	3
Year = 2007						
Manufacturing	33	26	21	178	2.9	3.2
Wholesale	42	24	45	177	1.5	4.3
Retail	8	15	40	562	0.7	0.4
Services	11	29	43	3103	5.9	3.9
Panel B: Average Annual Growth Rates (2008-2012)						
Manufacturing	0.4%	-0.3%	-3.0%	-3.2%	-5.7%	-2.0%
Wholesale	0.6%	1.0%	-2.7%	-2.3%	-9.4%	-2.7%
Retail	1.8%	-0.1%	-3.3%	-1.6%	-7.1%	-3.5%
Services	1.9%	0.0%	-0.8%	-0.1%	-7.2%	-5.0%
Panel C: Growth Rates between 2007-2012						
Manufacturing	1.9%	-1.4%	-14.8%	-15.8%	-28.4%	-10.1%
Wholesale	3.2%	5.2%	-13.7%	-11.6%	-46.3%	-13.5%
Retail	9.0%	-0.4%	-16.4%	-8.0%	-35.0%	-17.5%
Services	9.5%	0.0%	-3.8%	-0.3%	-35.6%	-25.1%

[a] Sectors are defined as the employment weighted NAICS 2 at the firm-level. For multi-unit firms, total employment are aggregated up to the NAICS2 level, and the firm-level sector is defined as NAICS code associated with the highest level of employment.

Table 3.5: Sectors of the Establishments of MNC and non-MNC

	2007			2012		
	US MNC	Foreign MNC	Non-MNC	US MNC	Foreign MNC	Non-MNC
Single sector firms ('000)						
Manufacturing	1.5	2.2	252	1	1.9	224
Wholesale	1.2	3.9	285	0.6	3.4	262
Retail	0.5	0.3	619	0.3	0.2	571
Services	5.4	3.6	3181	3.7	2.7	3170
Multiple sectors firms ('000)	2.5	1.8	21	2.2	1.7	19
% of firms in multiple sectors relative to total firm	22.7%	15.3%	0.5%	28.3%	17.2%	0.5%

[a] Sectors are defined at the establishment level.

Table 3.6: Number of Source Countries (Median Firm)

Panel A: Imports

	Year = 2007			Year = 2012		
	All Imports	Related Party	Non-Related Party	All Imports	Related Party	Non-Related Party
US MNC	5	1	4	6	1	6
Foreign MNC	3	1	3	4	2	3
importers only (non MNC)	1	0	1	1	0	1
Importers and Exporters (non MNC)	2	0	2	2	0	2

Panel B: Exports

	Year = 2007			Year = 2012		
	All Exports	Related Party	Non-Related Party	All Exports	Related Party	Non-Related Party
US MNC	7	1	7	10	1	9
Foreign MNC	3.5	1	3	4	1	4
Exporters only (non MNC)	1	0	1	1	0	1
Importers and Exporters (non MNC)	2	0	2	2	0	2

Table 3.7: Number of Products (Median Firm)

Panel A: Imports

	Year = 2007			Year = 2012		
	All Imports	Related Party	Non-Related Party	All Imports	Related Party	Non-Related Party
US MNC	12	6	11	16	7	15
Foreign MNC	13	9	9	15	10	10
importers only (non MNC)	2	1	2	2	1	2
Importers and Exporters (non MNC)	4	2	4	4	2	4

Panel B: Exports

	Year = 2007			Year = 2012		
	All Exports	Related Party	Non-Related Party	All Exports	Related Party	Non-Related Party
US MNC	11	5	10	15	8	14
Foreign MNC	7	3	7	8	3	7
Exporters only (non MNC)	1	1	1	1	1	1
Importers and Exporters (non MNC)	3	1	3	3	1	3

[a] Products are defined at the HS10 level.

Table 3.8: Aggregate Related Party Trade

Ratio of Related Party Imports/Total Imports

	2007	2012
US MNC	45.7%	41.2%
Foreign MNC	72.2%	69.1%
importers only (non MNC)	9.5%	10.3%
Importers and Exporters (non MNC)	21.1%	21.1%

Ratio of Related Party Exports/Total Exports

	2007	2012
US MNC	37.7%	35.9%
Foreign MNC	44.5%	43.8%
Exporters only (non MNC)	7.8%	12.9%
Importers and Exporters (non MNC)	11.2%	11.5%

Table 3.9: Annual Employment Growth Rates at the Firm Level

	Annual Employment Growth Rates			
	(1)	(2)	(3)	(4)
MNC	-0.00177	0.0514***		
	[0.00587]	[0.00519]		
US MNC			-0.00111	0.0516***
			[0.00592]	[0.00559]
Foreign MNC			-0.00426	0.0509***
			[0.00805]	[0.00617]
Observations	48000000	48000000	48000000	48000000
R-squared	0.002	0.257	0.002	0.257
Fixed Effects	Year	Cells	Year	Cells
Clustered SE	Year	Cells	Year	Cells

[a] In Columns (1) and (3), the regressions were estimated with year fixed effects. In Columns (2) and (4), the regressions were estimated using the fully saturated model, whereby the cells are constructed by interacting Age $\times$ Industry $\times$ Size $\times$ Multi-Unit $\times$ Year.
[b] Clustered standard errors are in parentheses.

Table 3.10: Firm Decomposition of Job Creation Rate (Weighted)

	Total Job Creation	Births	Acquisitions	Continuers
	Panel A: MNC Indicator			
MNC	0.0420***	0.0180***	0.0178***	0.00620***
	[0.00339]	[0.00173]	[0.00246]	[0.00172]
	Panel B: US and Foreign MNC Indicators			
US MNC	0.0403***	0.0180***	0.0170***	0.00531***
	[0.00378]	[0.00189]	[0.00272]	[0.00195]
Foreign MNC	0.0475***	0.0181***	0.0202***	0.00919***
	[0.00418]	[0.00209]	[0.00245]	[0.00296]
Observations	48,000,000	48,000,000	48,000,000	48,000,000

[a] Fixed effects are constructed by interacting Age × Industry × Size × Multi-Unit × Year.
[b] Clustered standard errors at Age × Industry × Size × Multi-Unit × Year level.

Table 3.11: Firm Decomposition of Job Destruction Rate (Weighted)

	Total Job Destruction	Deaths	Divestitures	Continuers
	Panel A: MNC Indicator			
MNC	-0.00945**	0.00319	-0.00832***	-0.00432**
	[0.00450]	[0.00203]	[0.00306]	[0.00182]
	Panel B: US and Foreign MNC Indicators			
US MNC	-0.0113**	0.0027	-0.00940***	-0.00459**
	[0.00491]	[0.00227]	[0.00325]	[0.00200]
Foreign MNC	-0.00336	0.00480**	-0.00473	-0.00343
	[0.00483]	[0.00230]	[0.00366]	[0.00225]
Observations	48,000,000	48,000,000	48,000,000	48,000,000

[a] Fixed effects are constructed by interacting Age × Industry × Size × Multi-Unit × Year.
[b] Clustered standard errors at Age × Industry × Size × Multi-Unit × Year level.

Table 3.12: Firm Decomposition of Churning Rate and Excess Reallocation Rate (Weighted)

	Churning	Excess Reallocation
	Panel A: MNC Indicator	
MNC	0.0325***	0.0241***
	[0.00606]	[0.00389]
	Panel B: US and Foreign MNC Indicators	
US MNC	0.0290***	0.0220***
	[0.00674]	[0.00437]
Foreign MNC	0.0442***	0.0309***
	[0.00660]	[0.00488]
Observations	48000000	48000000

[a] Fixed effects are constructed by interacting Age × Industry × Size × Multi-Unit × Year.
[b] Clustered standard errors at Age × Industry × Size × Multi-Unit × Year level.

Table 3.13: Sectoral Decomposition of Net Job Creation Rate (Weighted)

Sectors	Net Job Creation $JC_{it} - JD_{it}$	Share of Net Job Creation	Job Creation JC_{it}	Job Destruction JD_{it}
		MNC Indicator		
Manufacturing	0.0104***	0.21	0.00819***	-0.00222***
	[0.000440]		[0.000330]	[0.000300]
Wholesale	0.00308***	0.06	0.00422***	0.00115***
	[0.000440]		[0.000330]	[0.000300]
Retail	0.00687***	0.14	0.0023	-0.00456**
	[0.00249]		[0.00171]	[0.00222]
Services	0.0303***	0.60	0.0265***	-0.00383
	[0.00433]		[0.00277]	[0.00364]

[a] Each row represents separate regressions that are estimated at the sectoral level. The dependent variables are net job creation ($JC_{it} - JD_{it}$), gross job creation (JC_{it}) and gross job destruction (JD_{it}).

$$\textit{Dep Var}_{i,t} = \beta_0 + \beta_1 MNC_{i,t} + \nu_{i,t} + \epsilon_{i,t}$$

[b] Fixed effects are constructed by interacting Age × Industry × Size × Multi-Unit × Year.
[c] Clustered standard errors at Age × Industry × Size × Multi-Unit × Year level.

Table 3.14: Sectoral Decomposition of Net Job Creation Rate (Weighted)

Sectors	Net Job Creation $JC_{it} - JD_{it}$	Share of Net Job Creation	Job Creation JC_{it}	Job Destruction JD_{it}
		Panel A: US MNC		
Manufacturing	0.00918***	0.18	0.00712***	-0.00206**
	[0.00110]		[0.000559]	[0.000868]
Wholesale	0.00270***	0.05	0.00365***	0.000957***
	[0.000440]		[0.000366]	[0.000307]
Retail	0.00721***	0.14	0.00244	-0.00476*
	[0.00272]		[0.00190]	[0.00249]
Services	0.0317***	0.62	0.0262***	-0.00549
	[0.00465]		[0.00311]	[0.00390]
		Panel B: Foreign MNC		
Manufacturing	0.0145***	0.29	0.0117***	-0.00274*
	[0.00201]		[0.00111]	[0.00161]
Wholesale	0.00434***	0.09	0.00611***	0.00177**
	[0.000908]		[0.000693]	[0.000786]
Retail	0.00574***	0.11	0.00183	-0.00391**
	[0.00220]		[0.00146]	[0.00169]
Services	0.0257***	0.51	0.0274***	0.0017
	[0.00496]		[0.00351]	[0.00392]

[a] Each row represents separate regressions that are estimated at the sectoral level. The dependent variables are net job creation ($JC_{it} - JD_{it}$), gross job creation (JC_{it}) and gross job destruction (JD_{it}).

$$\textit{Dep Var}_{i,t} = \beta_0 + \beta_1 \textit{US MNC}_{i,t} + \beta_2 \textit{Foreign MNC}_{i,t} + \nu_{i,t} + \epsilon_{i,t}$$

[b] Fixed effects are constructed by interacting Age × Industry × Size × Multi-Unit × Year.
[c] Clustered standard errors at Age × Industry × Size × Multi-Unit × Year level.

Table 3.15: Annual Employment Growth, MNC and Related Party Trade Indicators (Weighted)

	Annual Employment Growth					
	All Sectors	Manufacturing	Wholesale Trade	Retail Trade	Services	NEC
	(1)	(2)	(3)	(4)	(5)	(6)
Main Effects						
US MNC	0.0457***	0.00440*	0.00531***	0.000426	0.0362***	-0.000603
	[0.0149]	[0.00226]	[0.00108]	[0.00742]	[0.0115]	[0.000471]
Foreign MNC	0.00453	-0.0267***	-0.00479	0.00841	0.029	-0.00139*
	[0.0257]	[0.00901]	[0.00315]	[0.00526]	[0.0222]	[0.000775]
Importer (RP)	0.0298***	0.00768***	0.00493***	0.00715**	0.00928*	0.000784**
	[0.00626]	[0.00124]	[0.000611]	[0.00326]	[0.00494]	[0.000354]
Importer (Non-RP)	0.118***	0.0309***	0.0129***	0.0144***	0.0592***	0.000907***
	[0.00360]	[0.00111]	[0.000549]	[0.00141]	[0.00278]	[0.000162]
Exporter (RP)	0.0226***	0.0141***	0.00226***	-0.00387	0.00992	0.000155
	[0.00746]	[0.00133]	[0.000564]	[0.00370]	[0.00625]	[0.000384]
Exporter (Non-RP)	0.0885***	0.0286***	0.0119***	0.0110***	0.0365***	0.000488***
	[0.00369]	[0.00109]	[0.000554]	[0.00133]	[0.00285]	[0.000151]
Related Party Trade MNC Differential						
US MNC × Importer (RP)	0.0146	0.00371**	-0.00307**	0.00832	0.00442	0.00125
	[0.0130]	[0.00181]	[0.00142]	[0.00799]	[0.00916]	[0.000853]
US MNC × Exporter (RP)	0.0107	-0.00244	0.00301	0.0112*	-0.00188	0.000859
	[0.0119]	[0.00186]	[0.00218]	[0.00577]	[0.00919]	[0.000622]
Foreign MNC × Importer (RP)	-0.00346	-0.000716	-0.00637*	-0.00714	0.00975	0.00102
	[0.0251]	[0.00426]	[0.00333]	[0.00474]	[0.0226]	[0.00105]
Foreign MNC × Exporter (RP)	0.016	0.00513	0.00684*	0.0157**	-0.0126	0.000997
	[0.0186]	[0.00402]	[0.00374]	[0.00694]	[0.0152]	[0.000930]
Non-Related Party Trade MNC Differential						
US MNC × Importer (Non-RP)	-0.0676***	-0.00805***	-0.00415***	-0.0147**	-0.0403***	-0.000344
	[0.0146]	[0.00210]	[0.00142]	[0.00676]	[0.0116]	[0.000673]
US MNC × Exporter (Non-RP)	0.00325	-0.00345	-0.00541***	0.00354	0.00837	0.000206
	[0.0149]	[0.00224]	[0.00142]	[0.00707]	[0.0115]	[0.000593]
Foreign MNC × Importer (Non-RP)	-0.00849	0.011	-0.0013	-0.00983**	-0.00909	0.000745
	[0.0201]	[0.00718]	[0.00272]	[0.00467]	[0.0166]	[0.00127]
Foreign MNC × Exporter (Non-RP)	-0.00327	0.0155**	0.00403	-0.00394	-0.0187	-0.000154
	[0.0345]	[0.00707]	[0.00491]	[0.00559]	[0.0316]	[0.00116]
Observations	48000000	48000000	48000000	48000000	48000000	48000000

[a] Fixed effects are constructed by interacting Age × Industry × Size × Multi-Unit × Year.
[b] Clustered standard errors at Age × Industry × Size × Multi-Unit × Year level.
[c] The variables *US MNC, Foreign MNC, Importer (RP), Importer (Non-RP), Exporter (RP) and Exporter (Non-RP)* are binary indicators.

Table 3.16: Annual Employment Growth, MNC and Log of Related Party Trade (Weighted)

	Annual Employment Growth					
	All Sectors	Manufacturing	Wholesale Trade	Retail Trade	Services	NEC
	(1)	(2)	(3)	(4)	(5)	(6)
Main Effects						
US MNC	0.0581***	0.00582**	0.00686***	0.000946	0.0452***	-0.000685
	[0.0135]	[0.00231]	[0.00110]	[0.00638]	[0.0106]	[0.000535]
Foreign MNC	0.0349	-0.0138*	0.00117	0.00880*	0.0401**	-0.00145**
	[0.0232]	[0.00725]	[0.00258]	[0.00451]	[0.0204]	[0.000740]
Log Imports (RP)	-0.000156	-0.000264**	5.15E-005	0.000351	-0.000345	5.03E-005
	[0.000522]	[0.000104]	[5.41e-05]	[0.000248]	[0.000448]	[3.22e-05]
Log imports (Non-RP)	0.00995***	0.00266***	0.00123***	0.00142***	0.00455***	9.59e-05***
	[0.000345]	[0.000105]	[5.15e-05]	[0.000183]	[0.000235]	[1.57e-05]
Log Exports (RP)	-0.000973	0.000198	-0.000233***	-0.000730*	-0.000198	-9.24E-006
	[0.000732]	[0.000121]	[5.12e-05]	[0.000419]	[0.000539]	[3.54e-05]
Log Exports (Non-RP)	0.00762***	0.00277***	0.00103***	0.000824***	0.00296***	3.93e-05**
	[0.000332]	[0.000109]	[4.90e-05]	[0.000123]	[0.000247]	[1.96e-05]
Related Party Trade MNC Differential						
US MNC X Log Imports (RP)	0.000568	0.000350**	-8.77E-005	-0.000174	0.000451	2.77E-005
	[0.00115]	[0.000174]	[0.000113]	[0.000704]	[0.000782]	[7.23e-05]
US MNC X Log Exports (RP)	0.00126	-0.000104	0.000423**	0.00067	0.000207	6.57E-005
	[0.000988]	[0.000155]	[0.000167]	[0.000488]	[0.000757]	[5.36e-05]
Foreign MNC X Log Imports (RP)	-0.000726	-8.29E-005	4.56E-005	-0.000656*	-6.62E-005	3.29E-005
	[0.00165]	[0.000374]	[0.000194]	[0.000381]	[0.00147]	[8.17e-05]
Foreign MNC X Log Exports (RP)	0.00219	-0.000237	0.000364	0.00136**	0.000607	9.18E-005
	[0.00134]	[0.000436]	[0.000308]	[0.000635]	[0.000934]	[7.69e-05]
Non-Related Party Trade MNC Differential						
US MNC X Log Imports (Non-RP)	-0.00420***	-0.000931***	-0.000436***	0.000199	-0.00305***	1.27E-005
	[0.00126]	[0.000157]	[9.79e-05]	[0.000816]	[0.000775]	[5.62e-05]
US MNC X Log Exports (Non-RP)	-0.00137	-0.000209	-0.000602***	-0.000441	-0.000131	1.38E-005
	[0.00111]	[0.000241]	[0.000138]	[0.000473]	[0.000873]	[6.47e-05]
Foreign MNC X Log Imports (Non-RP)	-0.00196	0.000183	-0.000656**	-0.000582	-0.000954	4.65E-005
	[0.00141]	[0.000489]	[0.000280]	[0.000419]	[0.00115]	[9.55e-05]
Foreign MNC X Log Exports (Non-RP)	-0.00209	0.00078	9.82E-006	-0.000512	-0.00235	-1.29E-005
	[0.00230]	[0.000574]	[0.000376]	[0.000451]	[0.00206]	[9.20e-05]
Observations	48000000	48000000	48000000	48000000	48000000	48000000

[a] Fixed effects are constructed by interacting Age × Industry × Size × Multi-Unit × Year.
[b] Clustered standard errors at Age × Industry × Size × Multi-Unit × Year level.
[c] The variables *US MNC and Foreign MNC* are binary indicators.

APPENDICES

APPENDIX A

Chapter 1

A.1 Dates of GSP Implementations and Renewals

Table A.1: GSP Implementations and Renewals

Effective Date	Date Expired	Period of Expiration (months)
October 30, 1984	July 4, 1993	
August 10, 1993	September 30, 1994	1
December 8, 1994	July 31, 1995	2
October 1, 1996	May 31, 1997	14
August 5, 1997	June 30, 1998	2
October 21, 1998	June 30, 1999	3.5
December 17, 1999	September 30, 2001	5.5

Source: (Jones, 2015)

A.2 Model Derivations

Formulating the Lagrangian and taking the first order conditions would yield the following expressions:

$$
\begin{aligned}
\mathcal{L} =& wL_i + \int_0^1 V_j Z_{ij} dj + \int_J \sum_k U_{jk}(1+\tau_{jk}) M_{ijk} dj + \lambda \left(Y_i - \Omega_i L_i^{1-\phi} X_i^{\phi} \right) \\
& + \psi \left(X_i - exp(\int_0^1 \gamma_j \log X_{ij} dj) \right) + \xi \left(X_{ij} - (Z_{ij}^{\frac{\epsilon}{1+\epsilon}} + \sum_k M_{ijk}^{\frac{\epsilon}{1+\epsilon}})^{\frac{1+\epsilon}{\epsilon}} \right)
\end{aligned}
$$

where the first order conditions are:

$$\partial L_i \quad : \quad w = (1-\phi)\lambda \frac{Y_i}{L_i} \tag{A.1}$$

$$\partial Z_{ij} \quad : \quad V_j = \xi \left(\frac{X_{ij}}{Z_{ij}} \right)^{\frac{1}{1+\epsilon}} \tag{A.2}$$

$$\partial M_{ijk} \quad : \quad U_{jk}(1+\tau_{jk}) = \xi \left(\frac{X_{ij}}{M_{ijk}} \right)^{\frac{1}{1+\epsilon}} \tag{A.3}$$

$$\partial X_{ij} \quad : \quad \xi = \phi \gamma_j \left(\frac{X_i}{X_{ij}} \right) \tag{A.4}$$

$$\partial X_i \quad : \quad \phi = \lambda \phi \left(\frac{Y_i}{X_i} \right) \tag{A.5}$$

An expression for X_{ij} is derived by combining (A.2) and (A.3) as follows:

$$M_{ijk} = Z_{ij} \left(\frac{V_j}{p_{jk}(1+\tau_{jk})} \right)^{1+\epsilon}$$

$$X_{ij} = \left[Z_{ij}^{\frac{\epsilon}{1+\epsilon}} + \sum_k Z_{ij}^{\frac{\epsilon}{1+\epsilon}} \left(\frac{V_j}{U_{jk}(1+\tau_{jk})}\right)^{1/\epsilon}\right]^{\frac{1+\epsilon}{\epsilon}} \tag{A.6}$$

$$\frac{X_{ij}}{Z_{ij}} = \left[1 + \sum_k \left(\frac{V_j}{U_{jk}(1+\tau_{jk})}\right)^{1/\epsilon}\right]^{\frac{1+\epsilon}{\epsilon}} = \left(\frac{V_j}{\phi\gamma_j\left(\frac{X_i}{X_{ij}}\right)}\right)^{1+\epsilon}$$

To obtain an expression for the marginal cost of the firm, I first define these two terms:

$$\tilde{U}_{jk} \equiv U_{jk}(1+\tau_{jk})$$
$$A_j \equiv 1 + (\frac{V_j}{\tilde{U}_{jk}})^{\epsilon}$$

Next, to derive the expression for the marginal cost, the optimal input choices are plugged into the production function and the equation is rearranged.

$$Y_i = \Omega_i \left(\frac{(1-\phi)\lambda Y_i}{w}\right)^{1-\phi} \left(\exp(\int_0^1 \gamma_j \log \lambda\phi Y_i(\frac{\gamma_i}{V_j})A_j^{1/\epsilon}\right)^{\phi}$$

$$MC_i = \lambda = \frac{1}{\Omega_i}\left(\frac{w}{1-\phi}\right)^{1-\phi}\left(\frac{\exp\int_0^1 \gamma_j \log(\frac{V_j}{\gamma_j})dj}{\phi}\right)^{\phi}\left(\frac{1}{\exp\int_0^1 \gamma_j \log A_j^{1/\epsilon}dj}\right)^{\phi}$$
$$= \frac{C_i}{\Omega_i B_i^{\phi}}$$

where $C_i = \left(\frac{w}{1-\phi}\right)^{1-\phi}\left(\frac{\exp\int_0^1 \gamma_j \log(\frac{V_j}{\gamma_j})dj}{\phi}\right)^{\phi}$ and $B_i = \exp\int_0^1 \gamma_j \log A_j^{1/\epsilon}dj$

The firm's import intensity from country k is given as:

$$\psi_k = \frac{\int_{J_0} \tilde{U}_{jk} M_{ijk} dj}{\lambda Y_i} = \frac{\phi}{A_j}\int_{J_0} \gamma_j (\frac{\tilde{U}_{jk}}{V_j})^{-\epsilon} dj$$

A.2.1 Substitution Effects

$$\begin{aligned}
\frac{\partial \log MC_i}{\partial \log(1+\tau_{jk})} =& -\phi \frac{\partial \log B_i}{\partial \log(1+\tau_{jk})} \\
=& \quad \phi \int_0^1 \frac{\gamma_j}{A_j} \left(\frac{\tilde{U}_{jk}}{V_j}\right)^{-\epsilon} \frac{1+\tau_{jk}}{\tilde{U}_{jk}} \frac{\partial \tilde{U}_{jk}}{\partial(1+\tau_{jk})} dj \\
=& \quad \phi \int_0^1 \frac{\gamma_j}{A_j} \left(\frac{\tilde{U}_{jk}}{V_j}\right)^{-\epsilon} \frac{1}{U_{jk}} \frac{\partial \tilde{U}_{jk}}{\partial(1+\tau_{jk})} dj \\
=& \quad \psi_k(1+\eta_{jk}) > 0 \\
\text{where} \qquad \eta_{jk} =& \quad \frac{1+\tau_{jk}}{U_{jk}} \frac{\partial U_{jk}}{\partial(1+\tau_{jk})} \geq 0
\end{aligned} \tag{A.7}$$

A.2.2 Scale Effects

The pass-through rate is derived as:

$$\begin{aligned}
p_i =& \quad \frac{\sigma_i}{\sigma_i - 1} MC_i \\
d\log p_i =& \quad d\log \mathcal{M}_\rangle + d\log MC_i + d\log(1+\tau_{jk})
\end{aligned} \tag{A.8}$$

Taking the natural logarithm of the components on the right-hand side of equation (A.8) and differentiating:

$$d\log \mathcal{M}_\rangle = \frac{\partial \log \mathcal{M}_\rangle}{\partial \log p_i}(d\log p_i - d\log P_k) = -\Gamma_i(d\log p_i - d\log P_k)$$

$$
\begin{aligned}
d\log MC_i =& d\log \frac{C_i}{\Omega_i} - \phi d\log B_i \\
d\log A_j =& \frac{\partial \log A_j}{\partial \log(\frac{U_j(1+\tau_{jk})}{V_j}}) d\log\left(\frac{U_j(1+\tau_{jk})}{V_j}\right) \\
=& -\frac{\epsilon}{A_j}\left(\frac{U_j(1+\tau_j)}{V_j}\right)^{-\epsilon} d\log\left(\frac{U_j(1+\tau_j)}{V_j}\right) \\
\phi d\log B =& \phi\int_0^1 \gamma_j d\log A_j^{1/\epsilon} dj \\
=& \phi\int_0^1 \frac{\gamma_j}{\epsilon}\left(\frac{-\epsilon}{A_j}\right)\left(\frac{U_j(1+\tau_{jk})}{V_j}\right)^{-\epsilon} d\log\left(\frac{U_j(1+\tau_{jk})}{V_j}\right) dj \\
d\log MC_i =& d\log \frac{C_i}{\Omega_i} + \phi\int_0^1 \frac{\gamma_j}{A_j}\left(\frac{U_j(1+\tau_{jk})}{V_j}\right)^{-\epsilon} d\log\left(\frac{U_j(1+\tau_{jk})}{V_j}\right) dj
\end{aligned}
$$

Putting them together:

$$
\begin{aligned}
d\log p_{ik} =& \frac{1}{1+\Gamma_{ik}}\left\{ d\log(\frac{C_i}{\Omega_i}) + \frac{\phi}{A_j}\int_0^1 \gamma_j \left(\frac{U_j(1+\tau_{jk})}{V_j}\right)^{-\epsilon} d\log\left(\frac{U_j(1+\tau_{jk})}{V_j}\right) dj \right\} \\
&+ \frac{\Gamma_{ik}}{1+\Gamma_{ik}} d\log P_k
\end{aligned}
$$

$$
\begin{aligned}
\frac{d\log p_{ik}}{d\log(1+\tau_{jk})} =& \frac{\Gamma_{ik}}{1+\Gamma_{ik}}\frac{d\log P_k}{d\log(1+\tau_{jk})} + \frac{1}{1+\Gamma_{ik}}\psi_k \frac{d\log(\frac{U_j(1+\tau_{jk})}{V_{jk}})}{d\log(1+\tau_{jk})} \\
=& \frac{\Gamma_{ik}}{1+\Gamma_{ik}}\left(\frac{d\log P_k}{d\log p_{ik}}\frac{d\log p_{ik}}{d\log(1+\tau_{jk})}\right) + \frac{1}{1+\Gamma_{ik}}\psi_k \frac{d\log(\frac{U_j(1+\tau_{jk})}{V_{jk}})}{d\log(1+\tau_{jk})} \\
=& \frac{\Gamma_{ik}}{1+\Gamma_{ik}}\left(S_{ik}\frac{d\log p_{ik}}{d\log(1+\tau_{jk})}\right) + \frac{1}{1+\Gamma_{ik}}\psi_k \frac{d\log(\frac{U_j(1+\tau_{jk})}{V_{jk}})}{d\log(1+\tau_{jk})} \\
=& 1 - \frac{\Gamma_{ik}}{1+\Gamma_{ik}} S_{ik} + \frac{1}{1+\Gamma_{ik}}\psi_k(1+\eta_{jk})
\end{aligned}
$$

Defining the following expression as:

$$1 + \eta_{jk} \equiv \frac{d \log(\frac{U_j(1+\tau_{jk})}{V_{jk}})}{d \log(1 + \tau_{jk})}$$

The scale effects can then be obtained as follows:

$$\begin{aligned}
q_i =& p_{ik}^{-\rho} P_k^{\rho-\nu} D_k \\
\frac{\partial \log q_i}{\partial \log(1 + \tau_{jk})} =& -\rho \frac{\partial \log p_{ik}}{\partial \log(1 + \tau_{jk})} + (\rho - \nu) \frac{\partial \log P_k}{\partial \log(1 + \tau_{jk})} \\
=& -\rho \frac{\partial \log p_{ik}}{\partial \log(1 + \tau_{jk})} + (\rho - \nu) \left(\frac{\partial \log P_k}{\partial \log p_{ik}} \frac{\partial \log p_{ik}}{\partial \log(1 + \tau_{jk})} \right) \\
=& -\rho \frac{\partial \log p_{ik}}{\partial \log(1 + \tau_{jk})} + (\rho - \nu) \left(S_{ik} \frac{\partial \log p_{ik}}{\partial \log(1 + \tau_{jk})} \right) \\
=& \left(-\rho + (\rho - \nu) S_{ik}\right) \left(1 - \frac{\Gamma_{ik}}{1 + \Gamma_{ik}} S_{ik} + \frac{1}{1 + \Gamma_{ik}} \psi_k (1 + \eta_{jk}) \right) \\
=& -\sigma_{ik} \left(1 - \frac{\Gamma_{ik}}{1 + \Gamma_{ik}} S_{ik} + \frac{1}{1 + \Gamma_{ik}} \psi_k (1 + \eta_{jk}) \right)
\end{aligned}$$

A.2.3 Total Effects

$$\begin{aligned}
\frac{\partial \log L_i}{\partial \log(1 + \tau_{jk})} =& \psi_k (1 + \eta_{jk}) - \sigma_{ik} \left(1 - \frac{\Gamma_{ik}}{1 + \Gamma_{ik}} S_{ik} + \frac{\psi_k (1 + \eta_{jk})}{1 + \Gamma_{ik}} \right) \\
=& \psi_k (1 + \eta_{jk}) \left(1 - \frac{\sigma_{ik}}{1 + \Gamma_{ik}} \right) - \sigma_{ik} \left(1 - \frac{\Gamma_{ik}}{1 + \Gamma_{ik}} S_{ik} \right)
\end{aligned}$$

Since $0 < \left(1 - \frac{\Gamma_{ik}}{1+\Gamma_{ik}} S_{ik}\right) < 1$, then $-\sigma_{ik} \left(1 - \frac{\Gamma_{ik}}{1+\Gamma_{ik}} S_{ik}\right) < 0$. For scale effects to dominate substitution effects, $\left(1 - \frac{\sigma_{ik}}{1+\Gamma_{ik}}\right)$ must be less than zero. That is,

$$\sigma_{ik} > 1 + \Gamma_{ik} \ .$$

The elasticity of demand for firm i must be relatively higher than the firm's markup elasticity with respect to its price.

A.2.4 Sign of $\dfrac{d\Lambda_0^*}{d(1+\tau_{jk})}$

This section shows the proof that $\dfrac{d\Lambda_0^*}{d(1+\tau_{jk})} < 0$. From the first-order conditions,

$$V_j\left(\frac{1}{1-\beta(1-\gamma)}+\Lambda_0\right) = \quad \xi\left(1+\left(\frac{V_j}{U_j(1+\tau_{jk})}\right)^{\epsilon}\right)^{1/\epsilon}$$

$$\Lambda_0^* = \quad \frac{\xi^*}{V_j}\left(1+\left(\frac{V_j}{U_j(1+\tau_{jk})}\right)^{\epsilon}\right)^{1/\epsilon} - \frac{1}{1-\beta(1-\gamma)}$$

Differentiating with respect to tariffs:

$$\frac{d\Lambda_0^*}{d(1+\tau_{jk})} = \quad \frac{\xi^*}{V_j}\left(1+\left(\frac{V_j}{U_{jk}(1+\tau_{jk})}\right)^{\epsilon}\right)^{\frac{1}{\epsilon}-1} \times$$

$$\left(\frac{V_j}{U_{jk}(1+\tau_{jk})}\right)^{\epsilon-1}\left(\frac{-V_j}{U_{jk}}(1+\tau_{jk})^{-2} - (\frac{V_j}{1+\tau_{jk}})U_{jk}^{-2}\frac{\partial U_{jk}}{\partial(1+\tau_{jk})}\right) < 0$$

A.2.5 Sign of $\dfrac{d\Lambda_1^*}{d(1+\tau_{jk})}$

From the first-order conditions, we have:

$$U_{jk}(1+\tau_{jk})\left(\frac{1}{1-\beta(1-\gamma)}+\Lambda_0\right) = \psi\gamma_j\frac{X}{X_j}\left(\frac{X_j}{M_{jk}}\right)^{\frac{1}{1+\epsilon}}$$

$$\frac{\sigma-1}{\sigma}Y^{\frac{\sigma-1}{\sigma}}\frac{\phi}{X}\left[\psi\gamma_j\frac{X}{X_j}\left(\frac{X_j}{M_{jk}}\right)^{\frac{1}{1+\epsilon}}\frac{1}{U_{jk}(1+\tau_{jk})} - \Lambda_1\right] = \psi$$

Solving for Λ_1^*:

$$\Lambda_1^* = \psi \left[\gamma_j \frac{X}{X_j} \left(\frac{X_j}{M_{jk}} \right)^{\frac{1}{1+\epsilon}} \frac{1}{U_{jk}(1+\tau_{jk})} - \frac{\sigma}{\sigma-1} \frac{X}{\phi} \frac{1}{Y^{\frac{\sigma-1}{\sigma}}} \right]$$

Solving for Y^*:

$$\begin{aligned}
\frac{1-\sigma}{\sigma}\frac{X}{L} =& \frac{w}{\psi}\left(\frac{1}{1-\beta(1-\gamma)} + \Lambda_0\right) \\
Y^* =& \Omega L^{1-\phi} X^{\phi} \\
=& \Omega \left(\frac{1-\phi}{\phi}\right)^{1-\phi} \left(\frac{\psi}{w\left(\frac{1}{1-\beta(1-\gamma)} + \Lambda_0\right)} \right)^{1-\phi} X
\end{aligned}$$

Plugging back to obtain Λ_1^*:

$$\Lambda_1^* = \psi \left\{ \gamma_j \frac{X}{X_j} \left(\left(\frac{1}{U_{jk}(1+\tau_{jk})} \right)^{\epsilon} + \frac{1}{V_J^{\epsilon}} \right)^{\frac{1}{\epsilon}} - \frac{\sigma}{\sigma-1} \frac{X^{\frac{1}{\sigma}}}{\phi} \frac{\left(\frac{1}{1-\beta(1-\gamma)} + \Lambda_0\right)^{(1-\phi)(\frac{\sigma-1}{\sigma})}}{\left[\Omega\left(\frac{1-\phi}{\phi}\right)^{1-\phi}\left(\frac{\psi}{w}\right)^{1-\phi}\right]^{\frac{\sigma-1}{\sigma}}} \right\}$$

Differentiating with respect to tariffs:

$$
\begin{aligned}
\frac{d\Lambda_1^*}{d(1+\tau)} =& \psi \Bigg\{ \gamma_j \Bigg[\underbrace{\frac{X}{X_j}\frac{1}{\epsilon}\left(\left(\frac{1}{U_{jk}(1+\tau_{jk})}\right)^{\epsilon}+\frac{1}{V_J^{\epsilon}}\right)^{\frac{1}{\epsilon}-1}(-\epsilon)U_{jk}^{-1}(1+\tau_{jk})^{-2}\frac{-1}{1+\tau_{jk}}\frac{dU_{jk}}{d(1+\tau_{jk})}}_{>0} \\
&+\underbrace{\left(\left(\frac{1}{U_{jk}(1+\tau_{jk})}\right)^{\epsilon}+\frac{1}{V_J^{\epsilon}}\right)^{\frac{1}{\epsilon}}\frac{1}{X_j}\frac{dX}{d(1+\tau_{jk})}}_{<0} \\
&+\underbrace{X\left(\left(\frac{1}{U_{jk}(1+\tau_{jk})}\right)^{\epsilon}+\frac{1}{V_J^{\epsilon}}\right)^{\frac{1}{\epsilon}}(-1)X_j^{-2}\frac{dX_j}{d(1+\tau_{jk})}}_{>0}\Bigg] \\
&-\frac{\sigma}{\sigma-1}\frac{1}{\phi}\frac{1}{\left(\Omega\left(\frac{1-\phi}{\phi}\right)^{1-\phi}\left(\frac{\psi}{w}\right)^{1-\phi}\right)^{\frac{\sigma-1}{\sigma}}}\times \\
&\Bigg[\underbrace{X^{\frac{1}{\sigma}}(1-\phi)\frac{\sigma-1}{\sigma}\left(\frac{1}{1-\beta(1-\gamma)}+\Lambda_0\right)^{(1-\phi)(\frac{\sigma-1}{\sigma})-1}\frac{d\Lambda_0^*}{d(1+\tau_{jk})}}_{<0} \\
&+\underbrace{\left(\frac{1}{1-\beta(1-\gamma)}+\Lambda_0\right)^{(1-\phi)(\frac{\sigma-1}{\sigma})}\frac{1}{\sigma}X^{\frac{1-\sigma}{\sigma}}\frac{dX}{d(1+\tau_{jk})}}_{<0}\Bigg]\Bigg\}
\end{aligned}
$$

For the above expression to be positive, the following condition must hold.

$$
\begin{aligned}
\frac{1}{X_j}\frac{dX}{d(1+\tau_{jk})}-\frac{X}{X_j^2}\frac{dX_j}{d(1+\tau_{jk})} &> 0 \\
\frac{dX}{d(1+\tau_{jk})} &> \frac{X}{X_j}\frac{dX_j}{d(1+\tau_{jk})} \\
\frac{dX}{d(1+\tau_{jk})}\frac{1+\tau_{jk}}{X} &> \frac{dX_j}{d(1+\tau_{jk})}\frac{1+\tau_{jk}}{X_j} \\
\epsilon_{X,\tau} &> \epsilon_{X_j,\tau}
\end{aligned}
$$

where $\epsilon_{X,\tau}$ and $\epsilon_{X_j,\tau}$ are, respectively, the elasticity of the intermediate input bundle X, and individual variety of intermediate input, X_j, with respect to tariff. Since the elasticities are negative, this relationship implies that X_j must be relatively more elastic (i.e. more negative). Intuitively, this condition is reasonable and follows similar logic to that of the household's nested demand function. Consider a manufacturing firm that produces clothing: its demand for textiles would be more inelastic relative to its demand for silk materials.

A.3 Measurement and Estimation Details

A.3.1 Estimation of Δb_t^i

I adopted the methodology employed in Trefler (2004) to construct Δb_t^i using two steps. First, the following regression is estimated using OLS for each industry separately.

$$\Delta y_t^i = \theta_0 + \sum_{j=0}^{J} \theta_j^i \Delta z_{t-j}^i + \eta_t^i \ ,$$

where $z_t^i \equiv (\log gdp_t, \log rer_t)$, with rer_t defined as the real exchange rate and gsp_t the gross domestic product at time t. Second, with the predicted values of Δy_t^i, i.e. $\hat{\Delta y_t^i}$, I define Δb_{post}^i as $\sum_{t=1996}^{1998} \hat{\Delta y_t^i}/3$; that is, the industry-specific prediction of the effect of business conditions on employment growth during the period associated with a GSP-shock. Likewise, I define Δb_{pre}^i as $\sum_{t=1993}^{1995} \hat{\Delta y_t^i}/3$ as the industry specific prediction of the effect of business conditions on employment growth during the period before the GSP shock.

A.3.2 Decomposition of Net Job Creation: Methodology

As is now standard in the study of business dynamics, the following definitions are used in the decomposition of net job creation into the different margins as discussed in the main text. First, at the establishment level, job creation (JC) and job destruction (JD) are defined as:

$$\begin{aligned} JC_{et} &= \max(g_{et}, 0) \\ JD_{et} &= \max(-g_{et}, 0) \end{aligned}$$

For establishments that newly enter in period t, the job creation rate would be $+2$, while for establishments that exit in period t, the job destruction rate would be -2.

To aggregate up to the firm level, we obtain the following expressions for the job creation and destruction at firm i.

$$JC_{it} = \sum_{e} \frac{X_{et}}{X_{it}} \max(g_{et}, 0) \tag{A.9}$$

$$JD_{it} = \sum_{e} \frac{X_{et}}{X_{it}} \max(-g_{et}, 0) \tag{A.10}$$

Equations (A.9) and (A.10) can separately be defined for different types of establishments within a firm. For continuers, the following expressions would apply.

$$JC_{it}^{cont} = \sum_{e \in cont} \frac{X_{et}}{X_{it}} \max(g_{et}, 0) \tag{A.11}$$

$$JD_{it}^{cont} = \sum_{e \in cont} \frac{X_{et}}{X_{it}} \max(-g_{et}, 0) \tag{A.12}$$

For new entrants through births or acquisitions,

$$JC_{it}^{birth} = \sum_{e} \frac{X_{et}}{X_{it}} \max(g_{et}, 0)\mathbf{1}(g_{et} = 2) \tag{A.13}$$

$$JC_{it}^{acquisition} = \sum_{e} \frac{X_{et}}{X_{it}} \max(g_{et}, 0)\mathbf{1}(g_{et} = 2) \tag{A.14}$$

For exits through deaths or divestitures,

$$JD_{it}^{death} = \sum_{e} \frac{X_{et}}{X_{it}} \max(-g_{et}, 0)\mathbf{1}(g_{et} = -2) \tag{A.15}$$

$$JD_{it}^{divestiture} = \sum_{e} \frac{X_{et}}{X_{it}} \max(-g_{et}, 0)\mathbf{1}(g_{et} = -2) \tag{A.16}$$

The main difference in distinguishing between job creation through births vis-à-vis through acquisitions is that the establishment identifiers (LBDNUM) associated with births would be new identifiers in the LBD. On the other hand, the LBDNUMs associated with acquisitions would have existed in the previous period, albeit being attributed to a different firm identifier (FIRMID). The same concept is applied in distinguishing between job destruction associated with deaths vis-à-vis divestitures. Establishment identifiers (LBDNUM) that belonged to the same firm i in period $t-1$ but no longer exist in the LBD in period t are deemed to be deaths. Meanwhile, LBDNUMs that switched firms, for example from firm x to firm y from period $t-1$ to t, are defined to be divestitures for firm x in period t.

APPENDIX B

Chapter 2

B.1 Data Descriptions and Variable Constructions

We adapted the methodology described in the NBER-CES Manufacturing Industry Database: Technical Notes (2013) and Kehrig (2015) in the construction of the variables used in this paper. The main establishment-level model objects that are required to calculate misallocation are physical productivity and the relative distortions on capital and labor. These model objects are calculated from the following data variables: value added, physical output, capital stock, and labor hours.

The ASM/CMF databases provide the establishment level measure of value added, VA_{ie}. We mapped the model object, $P_{ie}Y_{ie}$, to the variable VA_{ie} in the data. We do not observe the physical output, Y_{ie}, for all establishments in the ASM/CMF database and so, we inferred Y_{ie} from the measure of value added. Given that the establishments are monopolistically competitive and face downward sloping demand curves, establishments with high physical output must have a lower price. We follow Hsieh and Klenow (2009) and raise VA_{ie} to the power of $\sigma/(\sigma-1)$ to arrive at the measure of physical output.

The capital stock measure, K_{ie} is available in the ASM/CMF database and is derived based on the perpetual inventory equation (see Foster et al. (2008)):

$$K_{ie,t} = (1-\delta_{i,t-1})K_{ie,t-1} + I_{ie,t} \ ,$$

where $I_{ie,t}$ denotes investment at time t, and $\delta_{i,t}$ denotes the depreciation rate at the industry level i at time t.

The labor hours variable, L_{ie}, measures the number of hours worked by all employees in an establishment. This would include the hours of both production workers (PH) and non-production workers (NPH) (i.e. managers, supervisors). While the ASM/CMF provide measures of the hours of production workers, they do not, however, provide information about the hours of non-production workers. We backed out NPH from the information on wages of workers. In the ASM/CMF, the wages of all workers (SW) and of production workers (WW) are available. Therefore, the wage per production worker is given as WW/PH. Following Kehrig (2015), we assume that the wages for non-production workers are 150% of those for production workers. So, the estimated wage per non-production worker is given as $1.5 \times (WW/PH)$. Thus, our estimate for NPH is $(SW - WW)/(1.5 \times (WW/PH))$. We obtain the measure for labor hours as follows:

$$L_{ie} = PH_{ie} + NPH_{ie} = PH_{ie} + \frac{SW_{ie} - WW_{ie}}{1.5 \times \frac{WW_{ie}}{PH_{ie}}}$$

The reported values of wages in the ASM/CMF do not include workers' benefits. The Bureau Labor of Statistics (BLS) provided us with previously unpublished manufacturing industry sector cost estimates for wages and salaries and total benefits from the National Compensation Survey (NCS). Specifically, we obtained detailed data for the manufacturing industry sector (private industry sector) as defined by SIC and NAICS for the period spanning from 1987 through 2007. The NCS is a relatively small establishment survey that has varied in size over the years. In many SIC and NAICS codes, the sample size is too small to provide detailed industry estimates at either a 4-digit SIC (for earlier years) or 6-digit NAICS. Therefore, the estimates are calculated at higher levels of aggregation (2-digit SIC and 3-digit NAICS) and by pooling together five years of data. Since several years of data are pooled together to provide a proxy for a given year, we used the data in constant dollar values.

Before matching this dataset to our ASM/CMF data, we concord the BLS' wages and salaries (*Wages*) and total benefits (*Benefits*) dataset that are in SIC industry codes to the NAICS 2007 industry codes level, by employing the NAICS-to-SIC concordance from the BLS (`www.bls.gov/ces/naicstosic2.htm`). Using this standardized dataset, we calculate the total wages and benefits adjustment factor as *(Wages + Benefits)/Wages* for each industry code. We then multiplied the wages of all workers (SW) in the ASM/CMF dataset with this adjustment factor.

B.2 Proofs

B.2.1 Proof of Proposition 1

$$\frac{\overline{TFPR}_i}{TFPR_{ie}} = \left(\frac{P_iY_i}{P_{ie}Y_{ie}}\right)^{1-\beta_i} \left[\frac{\overline{MRPK}_i}{MRPK_{ie}}\right]^{\alpha_{K_i}} \left[\frac{\overline{MRPL}_i}{MRPL_{ie}}\right]^{\alpha_{L_i}}$$

The expression for the actual relative revenue productivity term is the weighted product of three terms: relative establishment size $\left(\frac{P_iY_i}{P_{ie}Y_{ie}}\right)$, the relative marginal revenue product of capital $\left(\frac{\overline{MRPK}_i}{MRPK_{ie}}\right)$ and the relative marginal revenue product of labor $\left(\frac{\overline{MRPL}_i}{MRPL_{ie}}\right)$. We show that each of these three terms could be rewritten using the relative distortions on factor inputs.

1. Relative establishment size

$$\begin{aligned}
\frac{P_{ie}Y_{ie}}{P_iY_i} &= \frac{\left[\frac{A_{ie}}{(1+\tau_{K_{ie}})^{\alpha_{K_i}}(1+\tau_{L_{ie}})^{\alpha_{L_i}}}\right]^{\frac{\sigma-1}{\beta_i+\sigma(1-\beta_i)}}}{\sum_{e'=1}^{N_i}\left[\frac{A_{ie'}}{(1+\tau_{K_{ie'}})^{\alpha_{K_i}}(1+\tau_{L_{ie'}})^{\alpha_{L_i}}}\right]^{\frac{\sigma-1}{\beta_i+\sigma(1-\beta_i)}}} \\
&= \frac{\left[\frac{A_{ie}}{(1+\tau_{K_{ie}})^{\alpha_{K_i}}(1+\tau_{L_{ie}})^{\alpha_{L_i}}}\right]^{\frac{\sigma-1}{\beta_i+\sigma(1-\beta_i)}}}{\sum_{e'=1}^{N_i}\left[\frac{A_{ie'}}{(1+\tau_{K_{ie'}})^{\alpha_{K_i}}(1+\tau_{L_{ie'}})^{\alpha_{L_i}}}\right]^{\frac{\sigma-1}{\beta_i+\sigma(1-\beta_i)}}} \times \left[\frac{\overline{(1+\tau_{K_i})}^{\alpha_{K_i}}\overline{(1+\tau_{L_i})}^{\alpha_{L_i}}}{\overline{(1+\tau_{K_i})}^{\alpha_{K_i}}\overline{(1+\tau_{L_i})}^{\alpha_{L_i}}}\right]^{\frac{\sigma-1}{\beta_i+\sigma(1-\beta_i)}} \\
&= \frac{\left[\frac{A_{ie}}{\left[\frac{(1+\tau_{K_{ie}})}{\overline{(1+\tau_{K_i})}}\right]^{\alpha_{K_i}}\left[\frac{(1+\tau_{L_{ie}})}{\overline{(1+\tau_{L_i})}}\right]^{\alpha_{L_i}}}\right]^{\frac{\sigma-1}{\beta_i+\sigma(1-\beta_i)}}}{\sum_{e'=1}^{N_i}\left[\frac{A_{ie'}}{\left[\frac{(1+\tau_{K_{ie'}})}{\overline{(1+\tau_{K_i})}}\right]^{\alpha_{K_i}}\left[\frac{(1+\tau_{L_{ie'}})}{\overline{(1+\tau_{L_i})}}\right]^{\alpha_{L_i}}}\right]^{\frac{\sigma-1}{\beta_i+\sigma(1-\beta_i)}}}
\end{aligned}$$

2. Relative marginal revenue product of capital

$$\frac{1}{\overline{MRPK_i}} = \sum_{f=1}^{N_i} \frac{1}{MRPK_{ie}} \frac{P_{ie}Y_{ie}}{P_iY_i} = \frac{1}{R} \sum_{f=1}^{N_i} \frac{1}{(1+\tau_{K_{ie}})} \frac{P_{ie}Y_{ie}}{P_iY_i} = \frac{1}{R} \frac{1}{\overline{(1+\tau_{K_i})}}$$

$$\frac{MRPK_{ie}}{\overline{MRPK_i}} = \frac{(1+\tau_{K_{ie}})}{\overline{(1+\tau_{K_i})}}$$

3. Relative marginal revenue product of labor

$$\frac{1}{\overline{MRPL_i}} = \sum_{f=1}^{N_i} \frac{1}{MRPL_{ie}} \frac{P_{ie}Y_{ie}}{P_iY_i} = \frac{1}{w} \sum_{f=1}^{N_i} \frac{1}{(1+\tau_{L_{ie}})} \frac{P_{ie}Y_{ie}}{P_iY_i} = \frac{1}{w} \frac{1}{\overline{(1+\tau_{L_i})}}$$

$$\frac{MRPL_{ie}}{\overline{MRPL_i}} = \frac{(1+\tau_{L_{ie}})}{\overline{(1+\tau_{L_i})}}$$

Putting the terms together, we can write the actual ratio of revenue productivity as a function of relative distortions on factor inputs and physical productivity.

$$\frac{\overline{TFPR_i}}{TFPR_{ie}} \propto \left\{ \left[\frac{\overline{1+\tau_{K_i}}}{1+\tau_{K_{ie}}} \right]^{\alpha_{K_i}} \left[\frac{\overline{1+\tau_{L_i}}}{1+\tau_{L_{ie}}} \right]^{\alpha_{L_i}} \frac{1}{A_{ie}^{(\sigma-1)(1-\beta)}} \right\}^{1/(\beta_i+\sigma(1-\beta_i))}$$

APPENDIX C

Chapter 3

C.1 Data Construction

C.1.1 Identifying Corporate Groups

C.1.1.1 Identifying MNCs using the Immediate Shareholder (ISH) variable

Recent papers have provided several reasons why the Immediate Shareholder (ISH) is a better indicator than the Global Ultimate Owner (GUO) in ascertaining if a firm is domestically-owned or foreign-owned. Notwithstanding the merits of the ISH, we wish to point out two instances when using the ISH alone can lead to misleading conclusions about the country of origin of the parent company. The first instance occurs when the firm and its ISH are located in the same country. In this case, the firm will look like a domestically-owned entity, even if it were to be an affiliate of a foreign multinational. The second instance is one in which the firm, its ISH and its GUO are located in three different countries. If we were to assume that the country where the ISH is located is the country of origin for the corporation, we will misidentify the firm's country of origin.

Consider the case of Samsung Electronics Co. Ltd. From Orbis, the ISH of Samsung Semiconductor Europe Limited is located in the United Kingdom. Hence, this procedure will determine that the firm is European while, in fact, the firm is Korean-owned. In another instance, a Samsung affiliate in Ukraine is immediately owned by Samsung Electronics Benelux, a holding company located in the Netherlands. In this case, the Ukraine subsidiary will be mistakenly classified as part of a Dutch-owned corporation.

Table C.1: Using the Immediate Shareholder (ISH) variable to identify MNCs (at the firm level)

Country	Number of Foreign Affiliates	Correctly classified as foreign-owned	Misclassified as domestically-owned	Correctly classified as foreign-owned but wrong country of origin
	(1)	(2)	(3)	(4)
AT	3,957	2,226	985	746
AU	1,489	650	669	170
BE	5,930	3,311	1,559	1,060
BG	959	555	189	215
CZ	5,163	3,488	596	1,079
DE	16,511	8,027	6,110	2,374
DK	2,023	1,197	475	351
ES	9,511	4,735	3,138	1,638
FI	2,386	1,555	442	389
FR	14,307	6,463	6,256	1,588
GB	22,162	7,834	11,602	2,726
GR	1,014	600	173	241
HU	1,713	1,377	53	283
IE	2,046	989	537	520
IT	8,918	4,298	2,796	1,824
JP	462	353	66	43
LT	728	508	72	148
LV	1,061	780	87	194
NL	5,836	2,231	2,840	765
NO	3,134	1,762	894	478
NZ	566	356	66	144
PL	7,456	4,690	1,240	1,526
PT	3,806	2,062	867	877
RO	4,501	3,153	413	935
RU	3,797	1,815	1,263	719
SI	838	584	78	176
SK	2,894	2,117	157	620
US	2,297	1,380	772	145

Note:This table shows the number of firms the immediate shareholder classify as locals and foreign owned. The first column of this table corresponds to the total number of firms in each country that are foreign owned. The second column corresponds to the number of firms whose ISH and GUO are located in the same origin country. The third column corresponds to the number of firms that the ISH define as locals, even when they are foreign owned. And finally, the fourth column shows the number of firms that are classified as a foreign owned companies, but from a different country than the one corresponding to the parent company.

Table C.1 shows the ability of the ISH to correctly classify the country of origin of a given firm. The first column of this table corresponds to the number of firms in each country that are foreign-owned. The second column corresponds to the number of firms that are correctly classified; i.e. firms whose ISH and GUO are located in the same country. The third column corresponds to the number of firms that the ISH define as domestically-owned, while, in fact, they are foreign-owned. Finally, the fourth column shows the number of firms that are classified as foreign-owned, but are from a different country than the one corresponding to the parent company. On average, almost half of the foreign affiliates in a given country are misclassified either as domestically-owned or foreign-owned but attributed to the wrong country of origin.

In Table C.2, we present the fractions of firms within a corporate group that are correctly classified, misclassified as domestically-owned, or correctly classified as foreign-owned but attributed to the wrong country of origin. Each column represents the number of countries in which the corporate group have operations. As seen from the table, for most countries, less than half of the firms within the corporate group are correctly classified as foreign (column 4–6). Nevertheless, for large corporations (measured in terms of the number of countries of operations) the fractions of firms in the corporate group that are correctly classified as foreign is higher.

There are also large cross-country variations in the proportions of affiliates within a corporation that are misclassified as domestic companies or correctly classified as foreign but from a different country of origin. The variation is more pronounced for corporations with presence in more than five countries. In Germany, an average of 10 percent of foreign affiliates in a corporate group are mistaken as domestic firms, while this fraction is nearly double in the United Kingdom. Similarly, in Austria, 7.2 percent of the affiliates within the corporation are assigned to a wrong country of origin, while this share is 17.2 percent for Greece and 38.6 percent for Ireland.

C.1.1.2 Identifying MNCs using the Global Ultimate Owner (GUO) variable

In general, the GUO indicator could serve three purposes: 1) to indicate which firm is the head of the corporation; 2) to serve as the umbrella for the group of firms which belong to a given corporate group; and 3) to determine the country of origin of the corporation. However, as described in the main text, the GUO that Orbis identified may not meet the criteria of a genuine parent firm as typically defined in economic models. First, many corporations have holding companies

Table C.2: Using the Immediate Shareholder (ISH) variable to identify MNCs (at the corporate-group level)

Country	No of corporate groups			% Correctly classified as foreign			% Misclassified as domestically owned			% Correctly classified as foreign-owned but wrong country of origin		
No. of country locations	$<= 3$	3-5	> 5	$<= 3$	3-5	> 5	$<= 3$	3-5	> 5	$<= 3$	3-5	> 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AT	756	89	111	40.7	53.9	52.2	2.3	5.7	10.1	0.7	4.0	7.2
AU	104	18	17	28.6	44.3	42.7	7.5	10.3	27.4	0.6	0.6	8.7
BE	566	78	80	32.4	37.8	40.8	5.1	11.1	19.3	1.0	4.6	10.4
BG	47	1	1	29.9	40.0	41.7	0.1	0.0	0.0	0.0	0.0	0.0
CZ	352	11	6	34.1	35.5	32.8	0.6	6.0	1.2	0.1	15.5	8.7
DE	2087	281	413	35.2	45.8	50.7	2.7	4.8	10.4	1.3	4.0	7.4
DK	542	98	98	44.2	58.7	59.1	2.7	4.5	13.1	0.1	2.3	4.5
ES	940	92	75	30.1	34.3	36.9	1.9	3.8	11.1	0.3	1.7	4.3
FI	265	39	59	29.4	41.2	51.3	3.0	8.7	12.7	0.3	2.3	4.6
FR	938	163	218	25.2	31.2	36.8	2.5	7.2	13.0	0.8	4.1	5.8
GB	834	137	206	24.6	23.8	27.7	4.7	12.2	20.3	1.4	6.8	12.7
GR	53	9	9	33.2	39.1	26.9	1.8	2.8	12.9	3.4	2.7	17.2
HU	12		3	28.3		40.0	2.2		30.9	0.0		1.4
IE	144	6	10	39.8	40.7	22.6	8.2	11.0	31.5	1.1	13.3	38.6
IT	1429	199	178	32.2	43.4	46.4	1.9	3.8	7.0	1.0	3.3	5.9
JP	358	111	249	26.1	34.1	38.0	1.2	3.7	8.5	1.0	4.9	10.2
LT	51	8	1	38.2	38.6	71.4	1.4	6.4	0.0	0.7	0.0	0.0
LV	46	1	1	40.4	60.0	50.0	1.8	0.0	0.0	0.0	0.0	0.0
NL	1037	115	130	37.7	44.7	44.8	3.9	9.1	21.7	0.5	2.3	9.9
NO	481	58	46	31.7	37.0	38.2	4.3	8.4	17.0	0.6	4.2	10.9
NZ	6		5	23.8		43.8	17.7		26.8	11.1		12.7
PL	99	15	15	29.7	34.4	31.6	1.6	7.1	8.0	0.7	5.5	8.9
PT	253	13	12	27.7	25.8	30.1	3.5	7.9	14.2	0.5	2.1	13.4
RO	27	2		41.8	30.6		1.2	0.0		0.0	0.0	
RU	63	5	9	18.6	11.4	3.7	2.2	6.3	2.8	1.5	15.5	9.5
SI	102	11	7	40.1	48.5	62.2	1.1	2.3	4.4	0.0	5.5	1.5
SK	95	2	4	36.5	33.0	26.5	3.8	0.0	7.9	1.0	0.0	6.3
US	300	85	339	27.4	28.1	33.5	15.1	26.5	27.7	7.7	18.5	28.0

Note: Each entry in this table corresponds to the fraction of firms within a corporation that are foreign owned and that are correctly classified as foreign firms (columns 4–6), misclassified as domestically owned firms (columns 7–9) or classified as foreign affiliates but from a different country of origin (columns 10–12). For each of this categories the information is reported separately by the number of countries in which the corporations holds operations: three or less countries (columns 1, 4, 7, and 10), more than three and less than five (columns 2, 5, 8, and 11), or more than five countries (columns 3, 6, 9, and 12).

that would be defined by Orbis as the GUO. These holding companies may also be located in tax haven economies. If the GUO variable is taken literally, we will observe many foreign affiliates in which their parent firms are located in tax haven economies[1]. Some examples include:

1. EATON CORPORATION PLC is an example of a large U.S. company based in Ireland (with operations in more than 40 countries and 160 affiliates).
2. EUROCHEM is located in Switzerland, but its GUO is in Bermuda (a small company that does services activities for the headquarter).
3. CENTAUR LUXCO SARL is the head of the corporation and is a very small company in terms of revenue with 77 subsidiaries worldwide. The address of the GUO is in Luxembourg but, in fact, it is an entertainment operator based in Madrid, Spain.

Second, Orbis considers financial ownership shares in determining a firm's GUO. As such, it is common for it to assign an international financial institution to be the parent of an industrial company. These financial institutions typically hold shares of the firm, but may not be involved in the strategic direction and management of the firm. Failure to correct for such cases can lead one to an inaccurate definition of corporate groups.

C.1.1.3 Defining the corporate groups

Given the above considerations, identifying the "true" parent company is challenging. The goal in this paper is more modest – we only need to accurately identify the firms that belong to the same corporate group and the location of the group's country of origin. Once the boundaries of the corporate groups are defined, we could determine the number of firms and the number of countries of operations associated with each corporate group. Specifically for each corporate group, we deduce these points from the location of the original GUO, total assets, number of employees, and the number of firms per country[2].

[1]These countries are: Anguilla, Antigua and Barbuda, Aruba, Bahamas, Barbados, British Virgin Islands, Cayman Islands, Dominica, Grenada, Montserrat, Netherlands Antilles, St. Kitts and Nevis, St. Lucia, St. Vincent and Grenadines, Turks and Caicos, U.S. Virgin Islands. Belize, Costa Rica, Panama, Hong Kong, Macau, Singapore, Andorra, Channel Islands (Guernsey and Jersey), Cyprus, Gibraltar, Isle of Man, Ireland, Liechtenstein, Luxembourg, Malta, Monaco, San Marino, Switzerland, Bermuda and Liberia.

[2]We show that in nearly all cases, the country with the highest concentration of assets is the country of origin of the corporate group.

C.1.2 Matching Orbis to Census

C.1.2.1 Step 1: Standardization of names and addresses

First, we clean the Orbis dataset of names and addresses of business units by correcting for common typos. For each observation, we used the SAS DQMATCH function to separately parse the organization's name and street address to create several versions of *match codes*. Essentially, a *match code* yields a condensed version of the character value, whereby the information content in each match code is determined by the sensitivity level. For higher levels of sensitivities, the two values must be very similar to produce the same match code. At lower levels of sensitivities, the two values may produce the same match codes despite some dissimilarities. In addition, we also employed the *SOUNDEX* function which encodes each word phonetically. This is useful to detect names and addresses that sound the same[3]. The same procedure is also employed for the corresponding variables in the Business Register (BR) at the U.S. Census for the years 2004 to 2012. Both the *match codes* and *SOUNDEX* codes are inputs for our matching procedure in the next step.

C.1.2.2 Step 2: Sequential matching based on different criteria of tightness

The goal of this step is to match the business entities from Orbis (broadly speaking, they would be considered as *firms*) with the list of *establishments* at the Business Register (BR). It is important, therefore, to note that many-to-one and one-to-many matches are very likely given that the definition of what constitutes a *firm* is likely to differ between the two datasets.

The Orbis dataset for a given year is first matched to the BR for that corresponding year. In addition, we have also used the BR for both the leading and lagging years in the matching procedure. This is motivated by the possibility that some observations in the Orbis dataset in a given year could correspond to the names and addresses of establishments in the BR either in the preceding or following year. For example, the information in Orbis in a given year might be one year lagged as the dataset might not have been updated.

Each establishment with a record in the BR contains both a physical address and a mailing address. Each matching criterion is matched first to the physical address in the BR. If unmatched, then we will follow up with another round of matching to the mailing address. After every match round, the establishments in the BR that are

[3] We refer the reader to the various SAS documents that describe these steps in greater detail. A good starting point is http://www2.sas.com/proceedings/forum2007/106-2007.pdf

successfully matched to an observation from the Orbis dataset would be removed from the list in the BR. Therefore, only establishments that are unmatched from the previous rounds will be used in the subsequent round of matching. See Table C.3 for details of our matching algorithm.

Table C.3: Matching Algorithm

	Versions							
	1	2	3	4	5	6	7	8
Organization Name								
First line of Name (Soundex)	×							
Second line of Name (Soundex)		×						
First line of Name (Match code at 85%)			×		×		×	×
Second line of Name (Match code at 85%)				×		×		
Address								
First line of Street Address (Soundex)	×	×						
First line of Street Address (Match code at 85%)			×	×				
Street Name (Match code at 85%)					×	×		
City name (Match code at 85%)							×	
State name (Match code at 85%)							×	
Zipcodes (Match code at 95%)	×	×						
Zipcodes (Match code at 80%)			×	×	×	×		×

Each version of our the matching algorithm would yield “cluster groups”. Firms from Orbis and establishments in the BR that are in the same cluster group would be deemed “matched”. Some matches are not unique since it is possible for several establishments in the BR to share nearly identical organization names and street addresses[4].

C.1.2.3 Step 3: Dealing with multiple matches

The outcome from the matching procedure above would be either unique matches (one Orbis firm matched to one BR establishment) or non-unique matches (one-to-many, many-to-one or many-to-many). To further clean the matches, we first

[4]This is due to the fact that the source information for the BR is the tax EIN. A large firm could potentially have several tax EINs.

removed all workplace cafeterias and parking services that are located in a business unit from the matches. In the BR, many workplace cafeterias and parking services are identified by the name of the "host" organization. To avoid such spurious matches, we removed the matches whereby the NAICS codes are given by "722514" (cafeterias) and "812930" (parking services). If the match is unique, no further cleaning is necessary. In all the other cases, the following cleaning procedures were implemented:

1. One (Orbis) to many (BR) matches
   Recall that we are interested in assigning ownership status of firms in the BR based on the ownership status in Orbis. In the case of one-to-many matches, we would assign the ownership information for the Orbis firm to all establishments that are matched in the BR. In other words, the BR matched establishments would inherit all the ownership information from the corresponding Orbis firm.

2. Many (Orbis) to many (BR) matches
   Within each cluster group, we would collapse the matches by FIRMIDs of the BR establishments. If this procedure yields a unique FIRMID within the cluster group, then this effectively becomes the case of the one-to-many matches and would be treated as such. If this continues to yield multiple FIRMIDs, then these matches are flagged for further manual checks.

3. Many (Orbis) to one (BR) matches
   These firms are flagged for further manual checks.

C.1.2.4 Step 4: Merging Orbis-BR matches with ownership links

From the previous step, most (but not all) of the firms in the Orbis-BR dataset is merged such that one FIRMID in the BR is matched to one firm in Orbis. For these firms, the ownership information for the Orbis firm (i.e. identity of the corporate group, country of origin, other members within the corporate group, etc.) would be assigned accordingly. For FIRMIDs in the BR that are merged to multiple Orbis firms, we exploit the corporate group identifier to pool these firms together. In other words, despite these many-to-many matches, this issue is no longer a complication as long as these BR firms do, in essence, belong to the same corporate group. This is a very likely outcome because large corporate groups tend to be matched to multiple FIRMIDs in the BR dataset. Any further remaining matches that could not be resolved are manually checked.

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