ESSAYS IN TRADE AND LABOR DEMAND

by

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to Kristen
for love, support, and inspiration

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CHAPTER I

Introduction

This dissertation consists of three distinct essays spanning the fields of trade and labor economics. The first essay integrates these two fields, examining the effects of trade liberalization on local labor market outcomes and workers' migration patterns. I develop a model of local labor markets that describes how tariff changes across industries affect wages in local labor markets within the liberalizing country. I then use these theoretical results to measure how Brazil's 1987-1995 trade liberalization affected wages and interstate migration within the country. I find that wages fell most in regions facing larger liberalization-induced price declines and that liberalization resulted in a substantial shift in migration patterns. These results demonstrate the empirical value of the theoretical framework and represent the first systematic evaluation of the effects of liberalization on internal migration.

The second essay focuses on capital-skill complementarity, a potentially important driver of increased income inequality. I argue that standard cost function estimates assuming quasi-fixed capital systematically overestimate the effect of capital-skill complementarity when subject to skill-biased technological change. I show that the bias results directly from cost minimizing behavior. I also develop a novel instrumental variables strategy based on the tax treatment of capital to accurately measure

the effect of complementarity, confirming the model's prediction that the standard approach overestimates the effect of complementarity.

The third essay, written with David Byrne and Ryan Michaels, examines the implications of global production sharing for measuring the price of semiconductors, a critical input to high-end domestic manufacturing and U.S. productivity growth. Our primary finding is that international shifts in the location of semiconductor wafer production toward lower-cost countries can result in unmeasured price declines of up to 0.8 percent per year. This finding has important implications for productivity measurement, since unmeasured price declines are likely to result in overstated productivity measurements in industries using semiconductor wafers as inputs to production.

CHAPTER II

Regional Labor Market Effects of Trade Policy: Evidence from Brazilian Liberalization

2.1 Introduction

Between 1988 and 1995, the Brazilian government abandoned a policy of import substitution in favor of drastic reductions in overall trade restrictions and a decrease in the variation of trade restrictions across industries. Along with the removal of non-tariff barriers, between 1987 and 1995 average tariffs fell from 54.9% to 10.8%, and the standard deviation of tariffs across industries fell from 21.3 to 7.4. Since the industrial composition of the labor force is quite varied across Brazilian states, the effects of trade liberalization were likely to have varying effects across different local labor markets in the country. In this paper, I develop a specific-factors model of regional economies to examine the relationships between trade liberalization and regional labor market outcomes. I then use the model's predictions to measure the liberalization's effect on wages in local labor markets and the effect on interstate migration patterns in Brazil.

I find that local labor markets whose workers are concentrated in industries facing the largest tariff cuts were negatively impacted by liberalization, relative to markets facing smaller cuts. Regions whose output faced a 10% larger liberalization-induced price decline experienced a 7% larger wage decline, relative to other regions. More-

over, I find that workers responded to this change in the geographic returns to work by shifting inter-state migration patterns, with increased migration flows out of states whose labor force faced the largest tariff cuts and into states facing smaller cuts. The most affected Brazilian states gained or lost approximately 2% of their populations as a result of liberalization-induced shifts in migration patterns. Both of these findings support the theoretical predictions of the specific-factors model of regional economies and confirm its value in guiding empirical specifications.

This is, to my knowledge, the first study to systematically evaluate the effects of national trade policy on internal migration.[1] The findings contribute to the empirical trade and local labor markets literatures in a number of ways. First, the results demonstrate a fundamental link between national trade policy and regional employment, housing, transportation, and poverty policy. The theoretical and empirical results imply that trade policy makers can use their knowledge of the pre-liberalization industrial mix of different regions to predict what regions are likely to see the largest wage changes and subsequent migration due to a proposed change in tariff structure. This will allow national governments pursuing large trade reforms to anticipate which regions will experience increased demand for infrastructure and public services, facilitating coordination of regional policies with changes in national trade policy.

Second, the model presented here provides a clear theoretical foundation in which to understand the circumstances under which national trade policies have disparate effects across different regions of a country. Previous empirical studies examining India's trade liberalization utilize the pre-liberalization industry mix of a re-

[1] Although Aguayo-Tellez, Muendler and Poole (2009) do not measure the effect of trade liberalization on internal migration, they demonstrate that globalization in general may influence workers' location choices, finding that Brazilian workers at exporting firms are less likely to migrate and that migrants tend to choose destinations with a high concentration of foreign-owned firms.

gion's workforce to determine how the region will be affected by a set of tariff changes (Topalova 2005, Edmonds, Pavcnik and Topalova 2007, Hasan, Mitra and Ural 2007, Hasan, Mitra and Ranjan 2009).[2] The model developed here provides a theoretical foundation for the use of pre-liberalization industry mix to infer the effects of subsequent tariff changes. In particular, the model provides guidance on how to treat the nontraded sector and yields predictions both for the sign of liberalization's effects, but also for their magnitudes. This allows for sharper tests of the mechanisms through which liberalization effects local labor markets, and the empirical results support the model's predictions quite closely.

Third, this paper contributes to a growing empirical literature evaluating the effects of Brazilian trade liberalization on labor market outcomes. Since Brazil's liberalization was large, quickly implemented, and well documented, it has been a fruitful ground for research on the relationship between trade policy and inequality.[3] This paper broadens the scope of this previous literature by examining the differential effects of liberalization across geographic regions of Brazil, rather than only considering country-wide impacts of liberalization.

Finally, the results complement the conclusions of previous work examining the effects of national shocks on local labor markets in the U.S. (Bartik 1991, Blanchard and Katz 1992, Bound and Holzer 2000). These studies examine the effects of changes in national industry mix on local labor markets, assuming that industry employment changes at the national level are exogenous to regional performance. This paper similarly maps national shocks into their regional effects, but contributes an explicit economic mechanism explaining the variation in national industry mix, showing that

[2] McCaig (2009) examines the effect of U.S. liberalization on labor market outcomes across Vietnamese regions, using a very similar empirical approach. To the extent that U.S. liberalization caused price changes faced by Vietnamese producers to vary across industries, the model developed here can be applied to that context as well.

[3] Goldberg and Pavcnik (2007) provide a summary, and more recent work includes Ferreira, Leite and Wai-Poi (2007) and Gonzaga, Filho and Terra (2006).

changes in national industry employment are driven by plausibly exogenous trade policy variation.[4] Since the specific-factors model of regional economies is based upon price changes across industries, it is not limited to examining liberalization. It can be applied to any situation in which national price changes drive changes in local labor demand.

The remainder of the paper is organized as follows. Section 2.2 develops a specific-factors model of regional economies in which industry price changes at the national level have disparate effects on wages in the country's different regional labor markets. Section 2.3 applies the specific-factors model in the context of trade liberalization and compares the resulting empirical specifications motivated by the model to those in previous work. Section 2.4 describes the data sets used, and Section 2.5 describes the specific trade policy changes implemented in Brazil's liberalization along with evidence in favor of the exogeneity of the tariff changes to industry performance. Section 2.6 presents an empirical analysis of the effects of trade liberalization on wages across local labor markets, and Section 2.7 demonstrates liberalization's impact on changes in interstate migration patterns in Brazil, both supporting the predictions of the model and finding economically significant effects of liberalization across regions. Section 2.8 concludes.

2.2 Specific-Factors Model of Regional Economies

This section develops a specific-factors model of regional economies in which industry price changes at the national level have disparate effects on wages in the country's different regional labor markets. Each region's endowment of industry-specific factors drives the equilibrium allocation of labor across industries and determines the effect of goods price changes on regional wages. In the baseline model, price changes

[4] See Figure 2.4 and the discussion in Section 2.5.

in industries that use a large amount of regional labor and have highly elastic labor demand will have the greatest impact on regional wages. Adding a nontraded sector to the model shows that local nontradables prices move with tradable prices, informing their empirical treatment. The section concludes by discussing the role of labor migration across regions in smoothing regional wage variation.

2.2.1 Baseline model

The baseline model treats each region within a country as a Jones (1975) specific-factors economy.[5] Consider a country with many regions, indexed by r. The economy consists of many industries, indexed by i. Production uses two inputs. Labor, L, is assumed to be mobile between industries, is supplied inelastically, and is fully employed. Labor is immobile between regions in the short run, but may migrate between regions in the long run (considered below). The second input, T, is specific to each industry in each region, i.e. it is not mobile between industries or regions. This input represents fixed characteristics of a region that increase the productivity of labor in the relevant industry. Examples include natural resource inputs such as mineral deposits, fertile land for agriculture, regional industry agglomerations that increase productivity (Rodriguez-Clare 2005), or fixed industry-specific capital.[6] All regions have access to the same technology, so production functions may differ across industries, but not across regions within each industry. Further, assume that production exhibits constant returns to scale. Goods and factor markets are perfectly competitive. All regions face the same goods prices, P_i, which are taken as given (endogenous nontradables prices are considered below).

[5] The specific-factors model is generally used to model a country rather than a region. In such a framework, the current model could be applied to a customs union in which all member countries impose identical trade barriers and face identical prices.

[6] An alternative interpretation of T is as a multiplicative productivity term on a concave production function taking L as an input. If production is assumed to be Cobb-Douglas, i.e. $Y = AT^{\alpha}L^{1-\alpha}$, one can see that variation in T^{α} is isomorphic to variation in the productivity term A.

When labor is immobile across regions, this setup yields the following relationship between regional wages and goods prices. Note that all theoretical results are derived in Appendix A (the following expression is (2.37) with labor held constant).

$$\hat{w}_r = \sum_i \beta_{ri} \hat{P}_i \qquad \forall r, \tag{2.1}$$

$$\text{where} \qquad \beta_{ri} = \frac{L_{ri} \frac{\sigma_{ri}}{\theta_{ri}}}{\sum_{i'} L_{ri'} \frac{\sigma_{ri'}}{\theta_{ri'}}}. \tag{2.2}$$

Hats represent proportional changes, σ_{ri} is the elasticity of substitution between T and L, and θ_{ri} is the cost share of the industry-specific factor T in the production of good i in region r. Note that each $\beta_{ri} > 0$ and that $\sum_i \beta_{ri} = 1 \; \forall r$, so the proportional change in the wage is a weighted average of the proportional price changes.

Equation (2.1) describes how a particular region's wage will be impacted by changes in goods prices. If a particular price P_i increases, the marginal product of labor will increase in industry i, thus attracting labor from other industries until the marginal product of labor in other industries equals that of industry i. This will cause an increase in the marginal product of labor throughout the region and will raise the wage. In order to understand what drives the magnitude of the wage change, note that for a constant returns production function, the labor demand elasticity equals $\frac{\sigma}{\theta}$.[7] The magnitude of the wage increase resulting from an increase in P_i will be greater if industry i is larger or if its labor demand is more elastic. Large industries and those with very elastic labor demand will need to absorb a large amount of labor from other industries in order to effect the decrease in the marginal product of labor necessary to restore equilibrium. Thus, price changes in these industries result in larger wage changes after the industrial reallocation of labor.

[7] Denoting the production function $F(T, L)$, and noting that T is fixed by definition, the labor demand elasticity is $\frac{-F_L}{F_{LL}L}$. Constant returns and Euler's theorem imply that $-F_{LL}L = F_{LT}T$. The elasticity of substitution for a constant returns production function can be expressed as $\sigma = \frac{F_T F_L}{F_{LT} F}$. Substituting the last two expressions into the first yields the desired result.

The relationship described in (2.1) captures the essential intuition behind this paper's analysis. Although all regions face the same set of price changes across industries, the effect of those price changes on a particular region's labor market outcomes will vary based on each industry's regional importance. If a region's workers are relatively highly concentrated in a given industry, then the region's wages will be heavily influenced by price changes in that regionally important industry.

2.2.2 Nontraded Sector

This subsection introduces a nontraded sector in each region, demonstrating that nontraded prices move with traded prices. This finding guides the empirical treatment of nontradables, which generally represent a large fraction of the economy under study. As in the baseline model, industries are indexed by $i = 1...N$. The final industry, indexed N, is nontraded, while other industries ($i \neq N$) are traded. The addition of the nontraded industry does not alter the results of the baseline model, but makes it necessary to describe regional consumers' preferences to determine the nontraded good's equilibrium price. I assume throughout that all individuals have identical homothetic preferences, permitting the use of a representative regional consumer. In particular, assume that each region's representative consumer has CES preferences over all goods and receives as income all wages and specific factor payments earned in the region.

When labor is immobile across regions, this setup yields the following relationship between the regional price of nontradables and tradable goods prices (the following expression is (2.63) with labor held constant).

$$\hat{P}_{rN} = \sum_{i \neq N} \xi_{ri} \hat{P}_i, \tag{2.3}$$

$$\text{where} \qquad \xi_{ri} = \frac{\frac{(1-\theta_{rN})}{\theta_{rN}}\sigma_{rN}\beta_{ri} + \varphi_{ri} + (\sigma-1)\mu_{ri}}{\sum_{i'\neq N}\frac{(1-\theta_{rN})}{\theta_{rN}}\sigma_{rN}\beta_{ri'} + \varphi_{ri'} + (\sigma-1)\mu_{ri'}}. \tag{2.4}$$

φ_{ri} is the share of regional production value accounted for by industry i, σ is the elasticity of substitution across goods in consumption (not to be confused with σ_{ri}, the elasticity of substitution in production), and μ_{ri} is the share of regional consumers' expenditure allocated to good i. Note that each $\xi_{ri} > 0$ and that $\sum_{i\neq N}\xi_{ri} = 1\ \forall r$, so the proportional change in the nontraded price is a weighted average of the proportional price changes for traded goods.

This finding is important in guiding the empirical treatment of the nontraded sector. Previous empirical studies of trade liberalizations' effects on regional labor markets pursue two different strategies. The first approach assumes no price change for nontraded goods, since trade liberalization has no direct impact on the nontraded sector. This approach is not supported by the theory, which predicts that nontraded prices move with traded prices. Artificially setting the price change to zero in the large nontraded sector would greatly understate the scale of liberalization's impact on regional wages. The second approach removes the nontraded sector from the weighted average in (2.1). This approach is more consistent with the theoretical findings. If the nontraded price changes by approximately the same amount as the average traded price, then dropping the nontraded price from (2.1) will have very little effect upon the overall average. Appendix A describes the conditions under which the nontraded sector will have exactly no affect on the overall average and can be omitted.[8] Ideally, one would simply calculate the terms in (2.4) using detailed data on production values and consumption shares across industries at the regional level. However, when data on regional production and consumption patterns are

[8]Omitting the nontraded sector will have no effect on the overall average when $\xi_{ri} = \frac{\beta_{ri}}{1-\beta rN}$. Appendix A demonstrates this fact and describes the restrictions under which the condition will hold exactly, though ξ_{ri} and β_{ri} are likely to be closely related in general, since part of the cross-industry variation in ξ_{ri} comes directly from β_{ri}, and φ_{ri} is also likely to be highly correlated with β_{ri}.

limited, the model implies that dropping the nontraded sector is likely to provide a close approximation to the ideal calculation.

2.2.3 Interregional Migration

Following a change in goods prices, the disparate wage effects across regions will change workers' incentives to locate in different regions. Workers can benefit by moving from regions whose wages were relatively negatively impacted and toward regions that were relatively positively impacted. This interregional migration will tend to equalize the impact of the price change across regions.

The mechanisms behind this equalization are demonstrated graphically in Figure 2.1, which represents a two-region ($r = 1, 2$) and two-industry ($i = A, B$) version of the baseline model.[9] Region 1 is relatively well endowed with the industry A specific factor. In each panel, the x-axis represents the total amount of labor in the country to be allocated across the two industries in the two regions, and the y-axis measures the wage in each region. Focusing on the left portion of panel (a), the curve labeled $P_A F_L^A$ is the marginal value product of labor in industry A, and the curve labeled $P_B F_L^B$ is the marginal value product of labor in industry B, measuring the amount of labor in industry B from right to left. Given labor mobility across sectors, the intersection of the two marginal value product curves determines the equilibrium wage, and the allocation of labor in region 1 between industries A and B, as indicated on the x-axis. The right portion of panel (a) is interpreted similarly for region 2. Although not necessary for any of the more general results, the figures are generated under the assumption of costless interregional migration for ease of exposition.

[9] Figure 2.1 was generated under the following conditions. Production is Cobb-Douglas with specific-factor cost share equal to 0.5 in both industries. $\bar{L} = 10$, $T_{1A} = 1$, $T_{1B} = 0.4$, $T_{2A} = 0.4$, and $T_{2B} = 1$. Initially, $P_A = P_B = 1$, and after the price change, $P_A = 0.5$.

Panel (a) of Figure 2.1 shows an equilibrium in which wages are equalized across regions. Since region 1 is relatively well endowed with industry A specific factor, it allocates a greater share of its labor to industry A when wages are equalized. Panel (b) shows the effect of a 50% decrease in the price of good A, so the marginal value product curve in both regions moves down halfway toward the x-axis. As described in (2.1), the impact of this price decline is greater in region 1, which allocated a larger fraction of labor to industry A than did region 2. Thus, region 1's wage falls more than region 2's wage. Now workers in region 1 have an incentive to migrate to region 2. For each worker that migrates, the central vertical axis moves one unit to the left, indicating that there are fewer laborers to be allocated in region 1 and more in region 2. As the central axis shifts left, so do the two marginal value product curves that are measured with respect to that axis. This shift raises the wage in region 1 and lowers the wage in region 2. Migration continues until regional wages are equalized.

The same equalizing effect of regional migration will occur in the more general model. The baseline model with variable labor demonstrates this effect (the following equation is (2.37) with prices held fixed).

$$\hat{w}_r = \frac{-1}{\sum_i \lambda_{ri} \frac{\sigma_{ri}}{\theta_{ri}}} \hat{L}_r, \tag{2.5}$$

where $\lambda_{ri} = \frac{L_{ri}}{L_r}$ is the fraction of regional labor allocated to industry i. This expression indicates that the aggregate regional labor demand elasticity is a weighted average of industry labor demand elasticities, with weights based on the allocation of labor across industries. As individuals migrate away from regions that were impacted relatively negatively by price changes and toward regions affected relatively positively, the wage difference between locations will shrink. In practice migration costs and other frictions make it unlikely that the cross-region wage variation gen-

erated by price changes will be entirely equalized. This expectation is supported by the wage analysis presented in Section 2.6, which finds evidence of some equalizing migration, but not enough to completely equalize cross-region wage impacts of liberalization.

Migration in the presence of nontraded goods poses two potential complications. First, when nontraded goods are present, each region's consumers face a unique price level and workers' migration decisions depend on the real wage change in a given location rather than the nominal change. Under the restrictions necessary to drop the nontraded sector from the weighted average in (2.1) described in Appendix A, when a given region experiences a nominal wage decline relative to another region, it will also experience a real wage decline relative to the comparison region.[10] In this situation nominal wage comparisons are sufficient to reveal real wage differences across regions, and the migration analysis can proceed using expressions for nominal wage changes as in (2.1). Second, the change in total income to residents of a given location determines the price change for regional nontradables. If specific factor owners migrate, it becomes very difficult to keep track of specific factor income transfers across regions. For simplicity, the analysis presented here assumes that migrants do not own specific factors, earning only wage income.

This section has described a specific-factors model of regional economies including many regions and many industries. The model yields predictions for the effects of goods price changes on regional wages, the prices of nontraded goods, and the incentives to migrate between regions. The framework developed here can be used

[10] In particular, the proportional change in a region's real wage, ω_r, can be expressed as follows:

$$\hat{\omega}_r = (1 - \mu_N)\hat{w}_r - \sum_{1 \neq N} \mu_i \hat{P}_i$$

where μ_i is industry i's share of consumption. The second term on the right hand side does not vary across regions and is irrelevant to interregional comparisons, while the first term is the nominal wage change scaled by the traded goods' share of consumption.

to measure the local impacts of any event in which a country faces price changes that vary exogenously across industries. I apply the model to the analysis of trade policy and devote the next section to operationalizing the model in the context of trade liberalization.

2.3 Applying the Model to Trade Liberalization

The previous section described a general framework linking national price changes to wage changes in regional labor markets. Here, I apply the model's insights to the question of how trade liberalization impacts local labor markets within the liberalizing country. I first link the model's price-based predictions to trade liberalization by describing the relationship between tariff changes and price changes when using industry-level data. Then I compare the resulting empirical framework to the previous literature on the local effects of liberalization. The model's predictions motivate empirical specifications that are similar to those in previous work, but exhibit some important differences regarding functional forms, the treatment of nontradables, and the interpretation of the magnitude of local effects.

2.3.1 Relating Tariff Changes to Price Changes

In order to use the specific-factors model in Section 2.2 to measure the effects of trade liberalization on local labor markets within the liberalizing country, I first need to determine how tariff cuts affected the prices faced by producers. For simplicity I make the small country assumption that tariff changes do not affect world prices (i.e. no terms of trade effects). In the Brazilian context, the researcher must use industry-level tariff and price data rather than information on tariffs and prices for individual goods (see Section 2.4 for more details). I address the issue of industry tariff pass-through by modeling industries as aggregations over a number of goods,

some of which face import competition while others do not. This simple aggregation strategy yields an estimation framework for measuring the effect of tariff changes on price changes at the industry level.

Starting with the result from the baseline model described in (2.1), make a slight change of notation. Industries i now consist of many goods g. Define $\mathbf{1}(ipc_{ig})$ as an indicator function for whether or not good g in industry i faces import price competition and P_{ig}^W as the world price. The price faced by producers is then,

$$P_{ig} = (1 + \tau_i)^{\mathbf{1}(ipc_{ig})} P_{ig}^W \tag{2.6}$$

For particular goods that are exported and thus do not face import price competition, $\mathbf{1}(ipc_{ig}) = 0$, and the price faced by producers equals the world price. For imported goods, $\mathbf{1}(ipc_{ig}) = 1$ and producers face the world price plus the tariff. Taking proportional changes,

$$\hat{P}_{ig} = \mathbf{1}(ipc_{ig})(1 \hat{+} \tau_i) + \hat{P}_{ig}^W. \tag{2.7}$$

Appendix B plugs this expression into (2.1) and aggregates from individual goods up to the industry level. The aggregation requires the additional restriction of Cobb-Douglas production (which was necessary for the empirical analysis in any case, since it is not feasible to calculate elasticities of factor substitution by industry and region). The result of the aggregation is

$$\hat{w}_r = \sum_i \beta_{ri}(\phi_{ri}(1 \hat{+} \tau_i) + \hat{P}_i^W), \tag{2.8}$$

where ϕ_{ri} is the fraction of industry i workers in region r producing goods that face import competition. As described below, the empirical analysis uses industry import penetration as a proxy for cross-industry variation in ϕ_{ri}. Import penetration measures are only available at the national level, and hence do not vary by region.

Accordingly, I assume constant import competition exposure across regions for a given industry, so $\phi_{ri} = \phi_i$. Imposing this restriction in (2.8), and comparing the result to (2.1), we have

$$\hat{P}_i = \phi_i(1 \hat{+} \tau_i) + \hat{P}_i^W. \tag{2.9}$$

Thus, tariff changes will have the largest effect on prices in industries facing large amounts of import competition (ϕ_i close to 1), and small effects on prices in export industries (ϕ_i close to 0).

2.3.2 Summary and Comparison to Previous Work

The specific-factors model of regional economies in Section 2.2 describes the relationship between the prices of tradable goods and regional wages. To understand the model's predictions for the local effects of trade liberalization, plug the price-tariff relationship from (2.9) into (2.1) (setting world price changes to zero), and drop the nontraded sector as discussed in Section 2.2.2. This yields the following expression describing the effect of tariff changes on regional wages.

$$\hat{w}_r = \sum_{i \neq N} \beta_{ri} \phi_i (1 \hat{+} \tau_i) \qquad \forall r, \tag{2.10}$$

$$\text{where} \qquad \beta_{ri} = \frac{L_{ri} \frac{\sigma_{ri}}{\theta_{ri}}}{\sum_{i' \neq N} L_{ri'} \frac{\sigma_{ri'}}{\theta_{ri'}}}. \tag{2.11}$$

The empirical analysis below uses this relationship to measure the effects of trade liberalization on regional wages and subsequent interregional migration.

The expression in (2.10) is quite similar to the empirical specifications employed in previous studies of the effect of liberalization on local market outcomes such as poverty, child labor, and unemployment in India (Topalova 2005, Edmonds et al. 2007, Hasan et al. 2007, Hasan et al. 2009), with some important differences. In these papers, changes in "district-level tariffs," τ_r^D, are computed as follows (using

present notation).[11]

$$\tau_r^D = \sum_i \delta_{ri} \Delta\tau_i \qquad \forall r \tag{2.12}$$

$$\text{where} \qquad \delta_{ri} = \frac{L_{ri}}{\sum_{i'=1}^{I} L_{ri'}}$$

Expressions (2.10) and (2.12) are both weighted averages of tariff changes with weights based (at least partly) on the region's industrial allocation of labor. However, a number of differences are present as well.

First, in (2.12) tariff changes are expressed as simple differences rather than proportional changes in $(1+\tau_i)$. For small τ_i, $\ln(1+\tau_i) \approx \tau_i$, so proportional changes may approximate changes in tariff levels.[12] Second, the tariff pass-through adjustment, ϕ_i, is omitted. Although this adjustment is essential when analyzing aggregate industry data in the Brazilian case, disaggregate data were used in the studies of India, so the pass-through adjustment may be less important in that context. Third, the weights omit the labor demand elasticity terms, $\frac{\sigma_{ri}}{\theta ri}$, essentially assuming that these terms are equal across all industries and regions. It is well beyond the scope of this paper to estimate elasticities of substitution between labor and other factors that vary across all industries and regions of Brazil, so I assume Cobb-Douglas production with factor shares free to vary across industries. This restriction implies that $\sigma_{ri} = 1$ and $\theta_{ri} = \theta_i$. I can calculate rough estimates of θ_i from Brazilian national accounts data and find that including them in the calculation of β_{ri} or omitting them does not substantially change the empirical results. Thus, although these differences should be accounted for in future work, none appears to cause economically significant deviations from the model's predictions.

The model also provides guidance on treatment of the nontraded sector. Topalova

[11] Note that Hasan et al. (2007) and Hasan et al. (2009) also use measures of non-tariff barriers.

[12] Although Brazil's liberalization involved large tariff cuts, making the approximation quite inaccurate, tariff changes based on tariff levels yield roughly the same ranking of industries as proportional changes in $(1+\tau_i)$, so the choice does not affect the sign of the results.

(2005) and Edmonds et al. (2007) estimate two versions of the weighted average in (2.12), one with the nontraded price change set to zero, and one dropping the nontraded sector, as in (2.10). The latter version is then used as an instrument for the former. Hasan et al. (2007) and Hasan et al. (2009) simply drop the nontraded sector and use that measure directly. As discussed in Section 2.2.2, the analysis presented here strongly favors dropping the nontraded sector. This measure should be used directly, omitting the version with zero nontraded price change entirely. Keep in mind that in cases where detailed production and expenditure data are available by region, the researcher can simply calculate the predicted tariff-induced nontraded price change in each region based on (2.3).

The theory-motivated approach clarifies the labor demand channel through which liberalization impacts regional labor markets and allows the researcher to carefully evaluate the magnitude of the effects of liberalization in testing the model's predictions. The model relates wage changes with tariff changes, and predicts a one-to-one relationship between proportional regional wage changes and the weighted average of tariff changes in (2.10). In the empirical analysis of Section 2.6, I examine this relationship directly, and find slightly smaller effects than the one-to-one relationship, as expected given some regional migration. Without the theoretical predictions, such a test of the sign and *magnitude* of local effects would not be possible. Thus, the theory allows the analysis to move beyond examining only the sign of estimates and provides a sharper test of the empirical model.

Given the many similarities, the model developed here provides a theoretical foundation for the general approach employed by previous empirical work on the local effects of liberalization. However, the differences just discussed provide important guidance on the appropriate implementation of empirical analyses. The remainder of

this paper tests the model's predictions regarding the impact of trade policy changes on regional wages and interregional migration patterns in the context of Brazil's 1987-1995 trade liberalization, and finds strong evidence supporting the model.

2.4 Data

Trade policy data at the Nível 50 industrial classification level (similar to 2-digit SIC) come from researchers at the Brazilian Applied Economics Research Institute (IPEA) (Kume, Piani and de Souza 2003), who aggregated tariffs on 8,750 - 13,767 individual goods, depending on the time period. Kume et al. (2003) also calculated effective rates of protection (ERP) from nominal tariffs and the Brazilian input-output tables, accounting for the effect of tariffs on final goods as well as tariffs on imported intermediate inputs. Given that ERP's account for intermediate inputs, the results use the ERP as the preferred measure of protection. All results were also generated using nominal tariffs without any substantive differences from those presented here.

Import penetration data, used to proxy for tariff pass-through adjustment in (2.9), were calculated from Brazilian National Accounts data available from the Brazilian Census Bureau (Instituto Brasileiro de Geografia e Estatistica - IBGE). Following Gonzaga et al. (2006), I measure import penetration as imports divided by the sum of imports and domestic production. Ferreira et al. (2007) implement a similar pass-through adjustment using import penetration data from Muendler (2003b), which is calculated using a slightly different formula. The results presented here have also been generated using these alternative import penetration adjustments without any substantive differences. Since Brazil does not calculate a producer price index (Muendler 2003a), I use the wholesale price index, IPA-OG maintained by Fundação

Getulio Vargas and distributed by IPEA. As a proxy for world prices, U.S. prices for manufactures come from the BLS Producer Price Index and agriculture prices from the USDA-NASS All Farm Index.

Wage data come from the long form Brazilian Demographic Censuses (Censo Demográfico) for 1991 and 2000 from IBGE. In both 1991 and 2000, the long form was applied to a 10% sample of households in municipalities whose estimated population exceeded 15,000 and a 20% sample in smaller municipalities (IBGE 2002). The survey is nationally representative and yielded sample sizes of approximately 4 million households consisting of 17 million individuals in 1991 and 5.3 million households consisting of 20.3 million individuals in 2000. The wage analysis presented in Section 2.6 uses the microregion as the geographic unit of observation. Each of 558 microregions is a grouping of economically integrated municipalities with similar geographic and productive characteristics (IBGE 2002). Wages are calculated as monthly earnings at the individual's main job divided by 4.33 times weekly hours at that job. The Census also reports employment status and industry of employment, which permits the calculation of the industrial distribution of labor in each microregion. While it would be ideal to have wage and employment information in 1987, just prior to liberalization, the wage analysis uses the 1991 Census as the baseline period under the assumption that wages and employment shares adjusted slowly to the trade liberalization.

Migration data come from the Pesquisa Nacional por Amostra de Domicílios (PNAD), a survey of Brazilian households conducted by IBGE. The survey has been conducted yearly since 1976 except census years (1980, 1991, 2000) and 1994. The survey is nationally representative, with the exception of the rural Northern region, corresponding to the Amazon rainforest. Since the survey is not representative of the

entire Northern region, which accounted for only 6.8% of the national population in 1991, I omit it from the empirical analysis. Figure 2.10 shows the states included in the migration analysis. Note that I combine Tocantins and the Distrito Federal into the state of Goiás in order to maintain consistent state classifications over time.[13] The PNAD sample size is approximately 100,000 households including roughly 300,000 individuals, covering about 0.2% of the population. The survey includes information on employment status and industry of employment, which permits the calculation of the industrial distribution of labor in each state. Migration data are available in the core survey from 1992 to the present. Questions include the current and previous state of residence and the years since the last interstate migration, topcoded at 10 years. Given that migration questions in the PNAD describe geography at the state level, I define "migration" as moving from one state to another.

In both the wage and migration analyses, I restrict the sample to individuals aged 18-55 in order to focus on people who are most likely to be tied to the labor force. In the migration analysis presented in Section 2.7, I also generate results that further restrict the sample based on employment and family status in an effort to abstract from issues of tied movers and family size. In order to utilize these disparate data sets in the analysis, it was necessary to construct a common industry classification that was consistent across data sources. The classification is based upon a crosswalk between the national accounts and PNAD industrial codes published by the IBGE (2004). The final industry classification consists of 21 industries, including agricultural and nontraded goods, shown in Table 2.1.

[13] Tocantins split from Goiás in 1988.

2.5 Trade Liberalization in Brazil

Brazil's large, quickly implemented, and well-documented trade liberalization in the early 1990's provides an excellent context in which to study the effects of trade policy changes on other economic outcomes. Brazil's liberalization generated substantial variation in tariff changes across industries by moving from a tariff regime with high tariff levels and high cross-industry tariff dispersion to a low level, low dispersion tariff regime. Qualitative and quantitative evidence supports the exogeneity of cross-industry variation in tariff changes to counterfactual industry performance, allowing causal interpretations of the subsequent empirical results using this variation.

2.5.1 Context and Details of Brazil's Trade Liberalization

From the 1890's to the mid 1980's Brazil pursued a strategy of import substituting industrialization (ISI). Brazilian firms were protected from foreign competition by a wide variety of trade impediments including very high tariffs, quotas, import bans on certain products, yearly maximum import levels per firm, assorted surcharges, prior authorization for imports of certain goods, and restricted credit for the purchase of imports (Abreu 2004a, Kume et al. 2003). Although systematic data on non-tariff barriers are not available, tariffs alone provide a clear picture of the high level of protection in 1987, just before liberalization. The average tariff level in 1987 was 54.9%, with values ranging from 15.6% on oil, natural gas, and coal to 102.7% on apparel. This tariff structure, characterized by high average tariffs and large cross-industry variation in protection, reflected a tariff system first implemented in 1957, with small modifications (Kume et al. 2003).

While Brazil's ISI policy had historically been coincident with long periods of

strong economic growth, particularly between 1930 and 1970, it became clear by the early 1980's that the policy was no longer sustainable (Abreu 2004a). Large amounts of international borrowing in response to the oil shocks of the 1970's followed by slow economic growth in the early 1980's led to a balance of payments crisis and growing consensus in government that ISI was no longer a viable means of generating sufficient economic growth. Between 1986 and 1987, Brazil ended a posture of obstruction in trade negotiations and began to seek concessions from trading partners in return for reductions in its own trade barriers (Abreu 2004b). It appears that this shift in trade policy came from within government rather than from the private sector. There is no evidence of political support from consumers of imported goods or of resistance from producers of goods losing protection (Abreu 2004b).

Tariff reforms began in late 1987 with a governmental Customs Policy Commission (Comissão de Politica Aduaneira) proposal of a sharp tariff reduction and the removal of many non-tariff barriers.[14] In June of 1988 the government adopted a weaker reform that lowered tariffs and removed some non-tariff barriers. In March 1990 import bans were eliminated, and firm-level import restrictions were removed in July 1991, so that by the end of 1991 tariffs represented the primary means of import protection. Between 1991 and 1994, phased tariff reductions were implemented, with the goal of reducing average tariff levels and reducing the dispersion of tariffs across industries in hopes of reducing the gap between internal and external costs of production (Kume et al. 2003). Following 1994, there was a slight reversal of the previous tariff reductions, but tariffs remained essentially stable following this period.

Figures 2.2 and 2.3 show the evolution of nominal tariffs and effective rates of

[14]See Kume et al. (2003) for a detailed account of Brazil's liberalization, from which this paragraph is drawn.

protection in the ten largest sectors by value added. Note that along with a general reduction in tariff levels, the dispersion in tariffs was also greatly reduced during liberalization, consistent with the goal of aligning domestic production incentives with world prices. Before liberalization, effective rates of protection were higher than nominal tariffs because of a graduated tariff structure that imposed higher tariffs on final goods than on imported intermediates. As the dispersion in the tariff structure fell during liberalization, the graduated structure was eliminated and effective rates of protection fell to approximately the same level as nominal tariffs.

It is clear in the figures that the move from a high-level, high-dispersion tariff structure to a low-level low-dispersion tariff distribution generated substantial variation in tariff changes across industries; industries with initially high tariffs experienced the largest tariff cuts, while those with initially lower tariff levels experienced smaller cuts. These large differences in tariff cuts across industries provide the identifying variation in the empirical analysis below and make Brazil an ideal context in which to study the differential impact of liberalization across regions with varying industrial distributions.

2.5.2 Exogeneity of Tariff Changes to Industry Performance

The empirical analysis below utilizes variation in tariff changes across industries. Figure 2.4 shows that industries facing larger tariff cuts shrank in terms of total workers employed, while industries facing smaller tariff cuts expanded their employment (The "tariff-induced price change," calculated based on (2.9) is described in detail in the next section).[15] Interpreted causally, this result implies that the cross-industry variation in tariff cuts generated changes in the national industry mix that may have induced workers to move from regions with many shrinking industries to

[15] A figure similar to Figure 2.4, appearing in Ferreira et al. (2007), provided the initial motivation for undertaking the present study.

regions with many growing industries. However, in order to make this causal claim, it is essential that the tariff changes were not correlated with counterfactual industry performance in the absence of liberalization. Such a correlation may arise if trade policy makers impose different tariff cuts on strong or weak industries or if stronger industries are able to lobby for smaller tariff cuts.

There are a number of reasons to believe that these general concerns were not realized in the specific case of Brazil's trade liberalization. As mentioned above, qualitative analysis of the political economy of liberalization in Brazil indicates that the driving force for liberalization came from government rather than from the private sector, and that private sector groups appear to have had little influence on the liberalization process (Abreu 2004a, Abreu 2004b). The 1994 tariff cuts were heavily influenced by the Mercosur common external tariff (Kume et al. 2003). Argentina had already liberalized at the beginning of the 1990's, and it successfully negotiated for tariff cuts on capital goods and high-tech products, undermining Brazil's desire to protect its domestic industries (Abreu 2004b). Thus, a lack of private sector interference and the importance of multilateral trade negotiations decrease the likelihood that the tariff cuts were managed to protect industries based on their strength or competitiveness.

More striking support for exogeneity comes from the nature of the tariff cuts during Brazil's liberalization. It was a stated goal of policy makers to reduce tariffs in general, and to reduce the cross-industry variation in tariffs to minimize distortions relative to external incentives (Kume et al. 2003). This equalizing of tariff levels implies that the tariff changes during liberalization were almost entirely determined by the pre-liberalization tariff levels. This pattern is apparent in Figure 2.6. Industries with high effective rates of protection before liberalization experienced the greatest

cuts, with the correlation between the pre-liberalization ERP level and change in ERP equaling -0.9.[16] The pre-liberalization tariff regime was based upon a tariff schedule developed in 1957 (Kume et al. 2003). Since the structure of the liberalization imposed cuts based on the tariff level that was set decades earlier, it is very unlikely that the tariff cuts were manipulated to induce correlation with counterfactual industry performance or with industrial political influence.

Finally, one can gain insight into the exogeneity of tariff changes by observing their relationship to industry growth. This relationship is demonstrated in Figure 2.4. As expected, industries facing larger tariff cuts shrank in terms of the number of workers employed in the industry, while those facing smaller tariff cuts grew. It is possible that certain industries were simply declining over time while others were growing, and that trade policy makers' choices were influenced by this observation[17]. However, this interpretation can be tested by observing the pattern of industrial reallocation during the time period immediately preceding liberalization. If trade policy choices were related to industrial performance, there should be a correlation between pre-liberalization industry employment growth and subsequent tariff changes. As shown in Figure 2.5, this is not the case. There is no relationship between the pre-liberalization employment growth and the subsequent tariff changes, supporting the argument that tariff changes were not related to industry performance and can be considered exogenous in the empirical analysis below.

2.6 The Effect of Liberalization on Regional Wages

Given the previous section's evidence supporting the exogeneity of tariff changes, I move to analyzing the effect of tariff changes on wages as predicted by the model

[16] The results for nominal tariffs are essentially identical, with a correlation of -0.95.

[17] This interpretation is somewhat implausible, since the observed pattern of tariff cuts were precisely the opposite of what one would expect if policy makers were trying to protect declining industries. The observed pattern would imply that policy makers cut tariffs most on declining industries that were most in need of protection

in (2.10). I first calculate the necessary terms and then test the model's prediction that regions facing larger tariff cuts experience larger wage declines relative to other regions. The results strongly confirm the model's prediction, implying that regions facing a 10% larger tariff decline experience 6.3%-7.6% larger wage declines. This finding is consistent with some equalizing interregional migration, motivating the subsequent migration analysis.

2.6.1 Regional Wage Changes

The model described in Section 2.2 considers homogenous labor, in which all workers are equally productive and thus receive identical wages in a particular region. In reality, wages differ systematically across individuals, and the wage change in a given region could be due changes in individual characteristics, changes in the returns to those characteristics, or changes in regional labor demand due to liberalization. In order to isolate the last effect, I calculate regional wage changes as follows. In 1991 and 2000 I separately estimate a standard wage equation, regressing the log of real wages on demographic and educational controls, industry fixed effects, and microregion fixed effects. The results of these regressions are reported in Table 2.2. I then calculate the regional wage change as the change in microregion fixed effects, plus a term reflecting the change in wages for an average 1991 individual. The addition of this average wage change term is purely for interpretation, as it does not vary across regions. It means that the regional wage change is interpreted as the proportional wage change an average 1991 individual would expect to face living in each microregion.

Figure 2.7 shows the regional wage changes in each microregion of Brazil. States are outlined in bold while each smaller area outlined in gray is a microregion. Microregions that are lighter experienced the largest wage declines during the 1991-2000

time period, while darker regions experienced the largest wage increases. As the scale indicates, some observations are quite large in magnitude. Happily, only 8 observations fall outside the ± 0.3 range, and these are all in sparsely populated areas, leading to imprecise estimates.

2.6.2 Tariff-Induced Price Changes

The discussion of industry aggregation in Section 2.3.1 suggests that tariff changes will have a larger impact on prices in industries where many of the goods comprising the industry face import competition. In particular, (2.9) suggests multiplying the tariff changes by the fraction of industry workers producing import-competing goods. This fraction is unknown, but we can proxy for it with industry import penetration, γ_i, calculated as imports divided by the sum of imports and domestic production.[18] Although I expect this measure to substantially understate the level of import competition in a given industry (i.e. $\gamma_i < \phi_i$), it is likely to capture the relative degree of import competition across industries. As a proxy for world prices in (2.9), I use U.S. prices. Using these proxies and allowing for random measurement error in prices u_i, the proportional change in the Brazilian price level π, and the proportional change in the Real-dollar exchange rate S, equation (2.9) becomes

$$\hat{P}_i = \pi + \gamma_i(1 \hat{+} \tau_i) + S + \hat{P}_i^{US} + u_i. \tag{2.13}$$

This relationship is estimated as

$$d\ln(P_i) = \psi_0 + \psi_1 \gamma_i d\ln(1+\tau_i) + \psi_2 d\ln(P_i^{US}) + u_i, \tag{2.14}$$

where d represents the long difference between 1997 and 1995, ψ_0 captures the effect of inflation and exchange rate changes, and ψ_1 is likely to be substantially larger than

[18] Alternative measures of import penetration have been used as well with no qualitative changes in results.

one given that import penetration understates the level of import price competition in each industry.

The results of estimating (2.14) are shown in Table 2.3. Columns (1) and (2) omit the tariff pass through term and find no relationship between tariff changes and price changes. This result is consistent with the findings of Gonzaga et al. (2006), and demonstrates the importance of the import penetration adjustment in capturing variable tariff pass through across industries. Columns (3) and (4) include the import penetration adjustment, finding a positive and statistically significant relationship between price changes and tariff changes. The estimate's large size suggests that import penetration does underestimate the scale of import competition, as expected. Letting hats represent estimates (rather than proportional changes as in the theory section), The tariff-induced price change is calculated as

$$d\ln\hat{(P_i)} = \hat{\psi}_1 \gamma_i d\ln(1+\tau_i). \tag{2.15}$$

By omitting $\hat{\psi}_0$ from this expression, tariff-induced price changes are calculated relative to changes in the overall price level. Figure 2.8 shows the tariff-induced price changes resulting from this calculation. Since these measures are normalized relative to the overall price level, they may be positive or negative in individual industries even though all tariffs were cut. This reflects the inherently cross-sectional nature of the empirical exercise. The goal is to measure the different effects of tariff changes on prices across industries rather than the overall effect of the liberalization on the price level.

2.6.3 Region-Level Tariff Changes

Based on (2.10), the effect of a given set of tariff changes on a region's wages is determined by a weighted average of tariff-induced price changes. In what follows, I

call this weighted average the "region-level tariff change." Calculating the β_{ri} terms in (2.11) requires information on the allocation of labor across industries and on labor demand elasticities. The industrial allocation of labor is calculated for each microregion from the 1991 Census. As mentioned above, it is not feasible to calculate elasticities of factor substitution across regions and industries, so I restrict production to be Cobb-Douglas. This implies that $\sigma_{ri} = 1$ and $\theta_{ri} = \theta_i$, which is calculated as one minus the wagebill share of industry value added using national accounts data from IBGE. Given these restrictions I calculate the region-level tariff change (RTC) for each microregion as follows.

$$RTC_r = \sum_{i \neq N} \beta_{ri} d\ln\hat{(P_i)} \tag{2.16}$$

$$\text{where} \qquad \beta_{ri} = \frac{L_{ri}\frac{1}{\theta_{ri}}}{\sum_{i' \neq N} L_{ri'}\frac{1}{\theta_{ri'}}}. \tag{2.17}$$

The results of this calculation appear in Figure 2.9. Lighter microregions faced the most negative tariff-induced price changes, while darker microregions faced more positive price changes. Recall that the tariff-induced price changes are calculated relative to the overall price level, so although all tariffs were cut, they may be positive or negative. This normalization is reflected here in the region-level tariff changes as well.

2.6.4 Wage-Tariff Relationship

Given the empirical estimates of the regional wage changes and region-level tariff changes, it is now possible to examine the effect of tariff changes on regional wages predicted by the specific-factors model. I form an estimating equation from (2.10) as

$$d\ln(w_r) = \zeta_0 + \zeta_1 RTC_r + \epsilon_r, \tag{2.18}$$

where $d\ln(w_r)$ is calculated as described in Section 2.6.1. Since these wage changes are estimates, I weight the regression by the inverse of the standard error of the estimates. RTC_r is given by (2.16). ζ_0 captures the increase in average real wages between 1991 and 2000. In the model without migration, the theory predicts that $\zeta_1 = 1$. As discussed in Section 2.2.3 any interregional mobility in response to liberalization will smooth out the regional wage variation that would have been observed on impact. In the extreme case of costless, instant worker mobility, all liberalization-induced wage variation would be immediately arbitraged away by worker migration and there would be no relationship between region-level tariff changes and regional wage changes. Since Brazil's population is particularly mobile (inter-state migration rates are similar to those in the U.S.), I expect some equalizing migration over the 9 year period being observed and thus expect that $0 < \zeta_1 < 1$. Finally, the error term ϵ_r captures any drivers of wage change that are unrelated to liberalization. In case of changes in state policies that may have influenced wages similarly across microregions within the state, I will also include state-level fixed effects.[19]

Table 2.4 presents the results of regressing the regional wage changes on the region-level tariff changes. As expected, the effect of region-level tariffs on regional wages is positive and statistically significant. This implies that microregions facing the largest tariff declines, as predicted by the model, did experience slower wage growth than regions facing smaller tariff cuts. The point estimates for ζ_1 are both less than 1, indicating the presence of some equalizing interregional migration.[20] The following section will examine migration patterns directly, corroborating this finding. The addition of state fixed effects lowers the magnitude of the point estimate somewhat, but remains qualitatively similar. In case of remaining covariance in the error term

[19] State-specific minimum wages were not implemented until 2002, so this does not confound the analysis.
[20] Although the estimate in column (1) is not statistically different from 1 at the 5% level

across microregions in a given state beyond a common additive component captured by the state fixed effects, I report standard errors clustered by state. This reduces the significance in column (1), but leaves the fixed effect specification essentially unchanged. Recall that these results are interpreted cross-sectionally - they do not measure the effect of liberalization on national wage growth or contraction, but rather describe the different effects of liberalization across regions of the liberalizing country. Thus, the estimate in column (2) implies that a region facing a 10% larger tariff decline will experience a 6.3% larger wage decline relative to other regions.

These results confirm the model's prediction, particularly in finding an estimate of the expected sign that is significantly different from zero, but below one. This supports the assumption that cross-region differences in the effects of liberalization are correctly measured and can be applied to other labor market outcomes of interest. The next section does this by examining the effects of liberalization on inter-state migration. The wage results also have implications for policy makers considering undertaking a large trade policy change, as they imply a clear link between trade policy decisions at the national level and local policy challenges. Given the predictions of the model, national policy makers could use the pre-liberalization distribution of labor across industries in different regions to determine what regions' workers are most likely to be negatively impacted by a proposed trade policy change. They can then coordinate with local policy makers to respond to the expected local impacts of the national policy change.

2.7 The Effect of Liberalization on Interstate Migration

The preceding section showed that trade liberalization caused substantial variation in wage changes across Brazilian microregions, and suggested that workers

responded by migrating away from locations facing the most negative wage changes to locations facing the most positive changes. This section directly measures the impact of liberalization on migration patterns utilizing detailed survey data on interstate migration from Brazil's yearly household survey. The results show that migration patterns changed as a result of liberalization, with more individuals moving away from states facing the largest tariff cuts and toward states facing smaller cuts. Counterfactual simulations imply that the most affected Brazilian states gained or lost approximately 2% of their populations as a result of liberalization-induced shifts in migration patterns.

2.7.1 Location Choice Specification

This section derives a framework for estimating the effect of tariff changes on individuals' location choice from a model of individual maximizing behavior. Although wages are an important aspect of location choice, other considerations such as local amenities, proximity to friends and relatives, and costs of moving to a particular location will also be relevant. These various aspects of location choice can be captured in the following additive random utility model.

$$U_{igdt} = V_{gdt} + \epsilon_{idgt} \tag{2.19}$$

$$V_{gdt} \equiv \alpha_g \ln w_{dt} + \mu_{gdt} + \eta_{gd} \tag{2.20}$$

U_{igdt} is the utility that individual i in group g (described below) receives from living in destination state d at time t. V_{gdt} represents the average utility individuals in group g receive from living in location d at time t, while ϵ_{idgt} represents individual idiosyncratic deviations from the average. The average utility in a given destination depends upon wages, w, and unobservable characteristics of the destination, some of which vary over time, μ_{gdt}, and some of which are fixed over time, η_{gd}.

The "group" subscript, g, determines how the unobservable terms in (2.20) vary. In this analysis, groups are always at least based upon state of residence, and potentially upon other demographic characteristics such as age or gender. Grouping by state of residence implies that the unobserved terms, μ_{gdt} and η_{gd}, vary by state pairs. Any moving costs associated with the distance between two states are therefore subsumed in these unobserved effects. Location-specific amenities such as natural beauty or urban nightlife will similarly be captured by these terms. Now suppose that groups are defined by state of residence and by age. This allows the value of these location-specific amenities to vary across age groups. Idiosyncratic variation in the utility of a particular location, due to the presence or absence of friends and relatives, desire for a change, or individual deviations from the average preferences of one's group, is captured in the error term ϵ_{idgt}. By careful group definition, the model can capture many rich and complex considerations that are relevant to location choice. The parameter of interest is α_g, the importance of wages in location decisions. Note that this parameter may also be assumed to vary across groups, as indicated by the group subscript. The empirical results presented below include specifications in which α is assumed constant across groups and others in which α_g may vary across groups.

Individuals compare all states and choose to live in the state that maximizes utility. Assuming that the ϵ_{idgt} are independently drawn from a Type I extreme value distribution, the probability π_{gdt} that an individual in group g chooses location d at time t is

$$\pi_{gdt} = \frac{e^{V_{gdt}}}{D_{gt}} \qquad \text{where} \quad D_{gt} \equiv \sum_{d'} e^{V_{gd't}}. \tag{2.21}$$

In the absence of the unobservable η_{gd} and μ_{gd} terms in V_{gdt}, this expression would reduce to a standard conditional logit model. Given that these unobserved terms cap-

ture the effects of distance, amenities, and other important aspects of location choice, dropping them is an unattractive alternative. In particular, if wages are correlated with these unobserved terms, omitting them and estimating a standard conditional logit model would yield inconsistent estimates of α_g. Thus, an alternative approach is necessary. I employ a strategy developed by Scanlon, Chernew, McLaughlin and Solon (2002) and adapted to the migration context by Cadena (2007) that differences out the time invariant unobserved characteristics through the use of a first-order Taylor series approximation. This process, implemented in Appendix C, yields the following equation.

$$d\ln S_{gd} - d\ln S_{gh} \approx \alpha_g(d\ln w_d - d\ln w_h) + \left[(d\mu_{gd} - d\mu_{gh}) + d\left(\frac{\xi_{gd}}{\pi_{gd}}\right) - d\left(\frac{\xi_{gh}}{\pi_{gh}}\right)\right] \tag{2.22}$$

Before describing the notation, replace the wage change terms with liberalization's effect on regional wages, the region-level tariff change (RTC), calculated in (2.16).

$$d\ln S_{gd} - d\ln S_{gh} \approx \alpha_g(RTC_d - RTC_h) + \left[(d\mu_{gd} - d\mu_{gh}) + d\left(\frac{\xi_{gd}}{\pi_{gd}}\right) - d\left(\frac{\xi_{gh}}{\pi_{gh}}\right)\right] \tag{2.23}$$

For simplicity, assume for the moment that g represents only state of residence, without any distinctions between demographic groups. S_{gd} is the observed share of individuals from state g choosing to locate in destination state d. The subscript h represents the current state of residence, or "home," so S_{gh} is the share of people from state g choosing to stay there rather than relocate. Thus the left hand side of (2.23) is the change in the share of individuals from g who choose to locate in d relative to the change in the share that choose to stay home. This difference-in-difference structure removes the time-invariant unobservables, η_{gd}. The independent variable of interest is the liberalization induced wage change in destination d, again relative to the same expression at home. Having an estimate of the coefficient on this term,

α_g, makes it possible to run counterfactual simulations describing how individuals would have moved under different circumstances. I do this below to measure the impact of liberalization on the distribution of population across Brazilian states. The term in brackets represents the error term, consisting of two parts. The first is the difference in time varying unobservable amenities. The presence of this expression in the error term makes clear the additional identification assumption necessary to estimate (2.23) in practice - changes in regional amenities must be uncorrelated with region-level tariff changes. This term also introduces a common error component across observations considering the same destination, so I calculate standard errors clustered by destination. ξ_{gd} is random sampling error in measuring S_{gd}, generating heteroskedasticity. I therefore weight by the square-root of the number of observations used to calculate S_{gd}.

2.7.2 Location Choice Results

I calculate region-level tariff changes by state (rather than by microregion as in the wage analysis) in the same manner as described in Section 2.6.3, the only difference being that employment shares were calculated using the 1987 PNAD rather than the Census. Figure 2.10 shows the results. The left hand side of (2.23) is calculated using migration data from the PNAD. Table 2.5 presents summary statistics regarding inter-state migration in Brazil among different demographic groups. The first column presents the fraction of the total population in each demographic group, while subsequent columns describe the fraction of individuals in each demographic group reporting different migration behaviors. Inter-state mobility in Brazil is very high. 29% of adults report having moved across states, which is nearly identical to the same figure in the U.S. (Dahl 2002). As a comparison to another large developing country, inter-state migration in Brazil is much more common than in India.

Topalova (2005) reports that only 3-4% of people migrated between Indian districts within a ten-year time period, whereas 9.7% of Brazilians report moving between states during a ten year period. Districts in India are very small compared to Brazilian states (on average each Indian state consists of 16 districts), so the difference in mobility is particularly striking.

The analysis compares individuals' location decisions just preceding trade liberalization (September 1982 - September 1988) to those just after liberalization (September 1996 - September 2002). The final two columns of Table 2.5 present the fraction of each demographic group that migrated in each of these periods. A number of patterns emerge. Consistent with the early observations of Sjaastad (1962) and nearly every subsequent study of migration, younger individuals are more likely to move. More educated individuals are more mobile, although the effect is not monotone over years of schooling, and those with larger families are far less mobile than individuals or couples. Whites and those of mixed heritage (reporting *Pardo*) are much more mobile than Blacks. Contrary to expectations, married people generally report more mobility than unmarried people, although the sample fractions are nearly equal in the post-migration period. These observations provide insight into what portions of the population are likely to be most mobile and therefore most likely to respond to changing geographic incentives by moving to a new location. These expectations are largely borne out in the empirical results.

The baseline results of estimating (2.23) are presented in Table 2.6. In the first row, grouping is by state of residence (source state) only. Thus, each observation represents a source-destination state pair. Since the equation for the share of individuals choosing to stay in the same state has been differenced from each observation, and there are 19 states included in the analysis, the total number of potential ob-

servations is $19 * 18 = 342$. The analysis drops any state pairs in which the share term, S_{gd}, was estimated using less than five underlying observations, so the realized number of observations is 168 rather than 342.[21] The estimate of α in the first row of Table 2.6 is 1.92. In order to assess the scale of this estimate, note that the estimating equation admits a convenient reduced-form interpretation that can be obtained by differentiating (2.21) with respect to $\ln w_{dt}$ for all d.

$$d\pi_{sd} = \alpha\pi_{sdt}\left((1-\pi_{sdt})d\ln w_d - \sum_{d'\neq d}\pi_{sd't}d\ln w_{d'}\right) \tag{2.24}$$

This expression describes how changes in wages across all regions affect the probability that an individual from state s will choose to locate in state d. Evaluating this expression at the estimate of α, the observed pre-liberalization migration fractions, and the tariff-induced wage changes given by (2.16), it is possible to calculate $d\pi_{sd}$ for each source-destination state pair. Then, by multiplying each of these estimates of the change in migration fraction by the relevant source state population in 1988 and summing over all sources for a given destination, it is possible to calculate the number of people accounted for by liberalization-induced shifts in the interstate migration pattern. The results of this exercise are shown in Table 2.7. The first column reports the number of people in each state that are accounted for by liberalization-induced shifts in migration patterns and the final column reports the same number as a fraction of the state's 1988 population. For those states facing the largest and smallest tariff cuts, liberalization accounts for gains or losses of approximately 2% of the state's population. Although not so large as to be implausible, this represents an economically significant shift in the Brazilian population's geographic distribution.

The remaining rows in Table 2.6 differ from the specification in the first row in that

[21] Since (2.23) requires taking logs of S_{gd}, group-destination bins containing zero observations, i.e. when no one in a particular group chooses a given destination, *must* be dropped. Although cells generated with 1-4 observations are technically usable, they are omitted in order to avoid wildly inaccurate estimates. A more stringent rule, dropping observations based on less than 10 underlying observations yield similar results.

grouping is based on state of residence (source) and on demographic characteristics. Given that group-destination pairs containing less than five underlying observations are dropped from the analysis, each demographic characteristic is separated into only two bins in order to avoid creating such fine grouping classifications that many group-destination pairs are dropped. When source state and demographic groups are considered, the number of potential observations is $19*18*2 = 684$. Although grouping by demographics increases the potential number of observations, the number of clusters (19) remains constant across all specifications, so demographic grouping does not inappropriately increase statistical power by "inventing" more observations. When grouping by demographic characteristics, two different specifications are considered. The first, labeled "homogeneous effect across groups," restricts the estimate of α to be constant across demographic groups, but does not place any restriction on the unobserved effects across demographic groups. Different age groups can value unobserved amenities differently even though α is constant across groups.

The second specification, labeled "heterogeneous effects across groups," allows α_g to vary across demographic groups, along with accounting for differences in unobserved effects across groups. In these specifications, it is expected that younger and more mobile individuals and those who are more connected to the labor market will exhibit stronger effects of location choice on tariff-induced wage changes, since these individuals have more to gain in expectation from choosing a new location. The results for age, gender, and family size all demonstrate the expected pattern - the more mobile group exhibits a stronger relationship (in statistical and economic terms) between tariff-induced wage changes and location choice. Note that the point estimates for the mobile groups are in a few cases much larger than the estimate from the first row considered above, indicating substantially larger liberalization-induced

migration responses for these demographic groups. The results for education in Table 2.6 are more surprising. Although those with fewer years of education are less mobile in general (see Table 2.5), less educated individuals exhibit a very strong location response to liberalization. The result may indicate that labor markets are segmented between high-skilled and lower-skilled workers, and that employers adjust to tariff changes primarily through changes in lower-skilled labor demand. This is an area for further study in a framework that accounts for worker heterogeneity in production.

These findings provide strong evidence that the disparate effects of trade liberalization on labor market conditions across Brazilian states led individuals to alter their location choices, moving away from states facing the largest tariff-induced price declines and toward states facing smaller cuts. The results also demonstrate the importance of accounting for variation in unobserved components of utility across demographic groups, and the fact that groups that are more mobile and more connected to labor market outcomes are most influenced by the geographic variation in the returns to work. As in the wage analysis, these results have important policy implications in linking trade policy decisions at the national level to local policy challenges. If a country's regions have different industrial compositions, then the adjustment to a large change in trade policy will necessarily involve some movement of workers from regions with many contracting industries toward regions with many growing industries. The results presented here show that the specific factors model of regional economies provides a means of predicting the pattern of interregional migration resulting from liberalization. Given this information, national policy makers can work at the local level to help individuals make the geographic transitions that necessarily come with a large industrial reorganization.

2.8 Conclusion

This paper develops a specific-factors model of regional economies addressing the local labor market effects of national price changes, and applies the model's predictions in measuring the effects of Brazil's trade liberalization on regional wages and interstate migration. The model predicts that wages will fall in regions whose workers are concentrated in industries facing the largest tariff cuts, and workers will then migrate away from these regions in favor of areas facing smaller tariff cuts. These predictions are confirmed by the empirical analysis. Regions whose output faced a 10% larger liberalization-induced price decline experienced a 7% larger wage decline. Liberalization also caused a substantial shift in migration patterns. The most affected Brazilian states gained or lost approximately 2% of their populations as a result of liberalization-induced shifts in migration patterns.

Given these results, it seems likely that liberalization has different local effects on other outcomes that could be studied in future work. For example, the framework presented here assumes full employment, so that all adjustment occurs through wages. In order to study the impact of liberalization on employment, the opposite assumption could be incorporated by fixing wages in the short run and allowing employment to adjust. Alternatively, Hasan et al. (2009) motivate their study of the effects of liberalization on local unemployment with a two-sector search model. An interesting avenue for future work would be to incorporate a search framework into a multi-industry model and directly derive an estimating equation relating changes in regional unemployment to tariff changes, paralleling the approach taken here. The model also suggests a novel channel through which liberalization could affect inequality. While the present analysis considered a homogenous labor force, future

work could examine the impact of trade liberalization in a situation with laborers of different skill levels working in industries of varying factor intensities. Particularly mobile groups of individuals will be able to smooth out regional wage variation by migrating while less mobile individuals will not. If the two groups work in segmented labor markets, liberalization could greatly increase national wage dispersion for the immobile group while leaving the mobile group's wages relatively unchanged.

This paper's findings have important implications in linking national policy changes, such as liberalization, to local policy challenges involving migration, transportation, and housing, as individuals migrate to restore geographic equilibrium. National policy makers can use the specific-factors model's predictions to assess what areas are likely to experience an influx of migrants hoping to gain employment in an area with many expanding industries and can mobilize local services to respond during the transition. On a larger scale, the migration results demonstrate a channel through which a country may reap the production gains from trade liberalization. Production gains can only occur by reallocating factors, and in countries with geographically distinct industrial distributions, a large scale industrial reallocation of labor requires laborers to migrate from one part of the country to another. Thus, relocation, transportation, and retraining services play an important role when pursuing a change in national policy that requires substantial industrial reallocation.

2.9 Appendix A: Specific Factors Model Solution

2.9.1 Factor prices

This section closely follows Jones (1975), but deviates from that paper's result by allowing the amount of labor available to the regional economy to vary. Consider a particular region, r, suppressing that subscript on all terms. Industries are indexed by $i = 1...N$. L is the total amount of labor and T_i is the amount of industry-specific factor for industry i available in the region. a_{Li} and a_{Ti} are the respective quantities of labor and specific factor used in producing one unit of industry i output. Letting Y_i be the output in each industry, the factor market clearing conditions are

$$a_{Ti}Y_i = T_i \qquad \forall i, \tag{2.25}$$

$$\sum_i a_{Li}Y_i = L. \tag{2.26}$$

Under perfect competition, the output price equals the factor payments, where w is the wage and R_i is the specific factor price.

$$a_{Li}w + a_{Ti}R_i = P_i \qquad \forall i \tag{2.27}$$

Let hats represent proportional changes, and consider the effect of price changes $\hat{P}_i$. θ_i is the cost share of the specific factor in industry i.

$$(1-\theta_i)\hat{w} + \theta_i\hat{R}_i = \hat{P}_i \qquad \forall i, \tag{2.28}$$

which follows from the envelope theorem result that unit cost minimization implies

$$(1-\theta_i)\hat{a}_{Li} + \theta_i\hat{a}_{Ti} = 0 \qquad \forall i. \tag{2.29}$$

Differentiate (2.25), keeping in mind that T_i is fixed in all industries.

$$\hat{Y}_i = -\hat{a}_{Ti} \qquad \forall i \tag{2.30}$$

Similarly, differentiate (2.26), let $\lambda_i = \frac{L_i}{L}$ be the fraction of regional labor utilized in industry i, and substitute in (2.30) to yield

$$\sum_i \lambda_i(\hat{a}_{Li} - \hat{a}_{Ti}) = \hat{L}. \tag{2.31}$$

By the definition of the elasticity of substitution between T_i and L_i in production,

$$\hat{a}_{Ti} - \hat{a}_{Li} = \sigma_i(\hat{w} - \hat{R}_i) \qquad \forall i. \tag{2.32}$$

Substituting this into (2.31) yields

$$\sum_i \lambda_i\sigma_i(\hat{R}_i - \hat{w}) = \hat{L}. \tag{2.33}$$

Equations (2.28) and (2.33) can be written in matrix form as follows.

$$\left[\begin{array}{cccc|c} \theta_1 & 0 & \dots & 0 & 1-\theta_1 \\ 0 & \theta_2 & \dots & 0 & 1-\theta_2 \\ \vdots & & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & \theta_N & 1-\theta_N \\ \hline \lambda_1\sigma_1 & \lambda_2\sigma_2 & \dots & \lambda_N\sigma_N & -\sum_i \lambda_i\sigma_i \end{array}\right] \left[\begin{array}{c} \hat{R}_1 \\ \hat{R}_2 \\ \vdots \\ \hat{R}_N \\ \hline \hat{w} \end{array}\right] = \left[\begin{array}{c} \hat{P}_1 \\ \hat{P}_2 \\ \vdots \\ \hat{P}_N \\ \hline \hat{L} \end{array}\right] \tag{2.34}$$

Rewrite this expression as follows for convenience of notation.

$$\left[\begin{array}{c|c} \Theta & \theta_L \\ \hline \lambda' & -\sum_i \lambda_i\sigma_i \end{array}\right] \left[\begin{array}{c} \hat{R} \\ \hline \hat{w} \end{array}\right] = \left[\begin{array}{c} \hat{P} \\ \hline \hat{L} \end{array}\right] \tag{2.35}$$

Solve for $\hat{w}$ using Cramer's rule and the rule for the determinant of partitioned matrices.

$$\hat{w} = \frac{\hat{L} - \lambda'\Theta^{-1}\hat{P}}{-\sum_i \lambda_i\sigma_i - \lambda'\Theta^{-1}\theta_L} \tag{2.36}$$

Note that the inverse of the diagonal matrix Θ is a diagonal matrix of $\frac{1}{\theta_i}$'s. This yields the effect of goods price changes and changes in regional labor on regional wages:

$$\hat{w} = \frac{-\hat{L}}{\sum_{i'} \lambda_{i'} \frac{\sigma_{i'}}{\theta_{i'}}} + \sum_i \beta_i \hat{P}_i \tag{2.37}$$

$$\text{where} \qquad \beta_i = \frac{\lambda_i \frac{\sigma_i}{\theta_i}}{\sum_{i'} \lambda_{i'} \frac{\sigma_{i'}}{\theta_{i'}}} \tag{2.38}$$

This expression with $\hat{L} = 0$ yields (2.1). Changes in specific factor prices can be calculated from wage changes by rearranging (2.28).

$$\hat{R}_i = \frac{\hat{P}_i - (1-\theta_i)\hat{w}}{\theta_i} \tag{2.39}$$

Plugging in (2.37) and collecting terms yields the effect of goods price changes and changes in regional labor on specific factor price changes.

$$\hat{R}_i = \frac{(1-\theta_i)}{\theta_i} \frac{\hat{L}}{\sum_{i'} \lambda_{i'} \frac{\sigma_{i'}}{\theta_{i'}}} + \left(\beta_i + \frac{1}{\theta_i}(1-\beta_i)\right) \hat{P}_i - \frac{(1-\theta_i)}{\theta_i} \sum_{k \neq i} \beta_k \hat{P}_k \tag{2.40}$$

Setting $\hat{L} = 0$ in (2.37) and (2.40) yields the equivalent expressions in Jones (1975).

2.9.2 Nontraded goods prices

As in the previous section, consider a particular region, omitting the r subscript on all terms. Industries are indexed by $i = 1...N$. The final industry, indexed N, is nontraded, while other industries ($i < N$) are traded. The addition of a nontraded industry does not alter the results of the previous section, but makes it necessary to describe regional consumers' preferences to fix the nontraded good's equilibrium price.

Assume a representative consumer with CES preferences over goods from each industry. This implies the following goods demands.

$$Y_i^c = \left(\frac{\alpha_i}{P_i}\right)^{\sigma} \frac{m}{\sum_j \alpha_j^{\sigma} P_j^{1-\sigma}}, \tag{2.41}$$

where Y_i^c is consumer demand, m is total consumer income, α_i is the CES share parameter, σ is the elasticity of substitution in consumption (not to be confused with σ_i, which is the elasticity of substitution between factors of production), and P_i

is the good's price. To simplify future expressions, define $\bar{P}$ as the CES price index,

$$\bar{P} \equiv \left(\sum_i \alpha_i^\sigma P_i^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \tag{2.42}$$

Substituting this into (2.41) and calculating the proportional change in Y_i^c yields

$$\hat{Y}_i^c = \hat{m} - \sigma \hat{P}_i + (\sigma - 1)\hat{\bar{P}}, \tag{2.43}$$

where hats represent proportional changes. The goal of the remaining steps is to express the terms of (2.43) in terms of price changes and changes in labor.

Change in the Price Level. Given the definition of $\bar{P}$,

$$\hat{\bar{P}} = \sum_i \mu_i \hat{P}_i \tag{2.44}$$

$$\text{where} \qquad \mu_i \equiv \frac{\alpha_i^\sigma P_i^{1-\sigma}}{\sum_j \alpha_j^\sigma P_j^{1-\sigma}}. \tag{2.45}$$

Change in Consumer Income. Consumer income equals total factor payments, so

$$\hat{m} = \eta_L(\hat{w} + \hat{L}) + \sum_i \eta_i \hat{R}_i, \tag{2.46}$$

where η_L and η_i are, respectively, the share of labor earnings and industry i specific factor earnings in total income. Substituting (2.37) and (2.40) into (2.46) and collecting terms yields

$$\begin{aligned} \hat{m} \;=\; & \underbrace{\sum_i \eta_L \beta_i \hat{P}_i + \sum_j \eta_j \beta_j \hat{P}_j + \sum_j \eta_j \sum_{k \neq j} \beta_k \hat{P}_k}_{\mathcal{X}} + \underbrace{\sum_j \frac{\eta_j}{\theta_j} (1 - \beta_j) \hat{P}_j - \sum_j \frac{\eta_j}{\theta_j} \sum_{k \neq j} \beta_k \hat{P}_k}_{\mathcal{Y}} \\ & + \underbrace{\left(\eta_L \left(\sum_i \lambda_i \frac{\sigma_i}{\theta_i} - 1 \right) + \sum_i \eta_i \frac{(1 - \theta_i)}{\theta_i} \right) \frac{\hat{L}}{\sum_i \lambda_i \frac{\sigma_i}{\theta_i}}}_{\mathcal{Z}} \end{aligned} \tag{2.47}$$

Examining the group of terms labeled $\mathcal{X}$,

$$\begin{aligned}
\mathcal{X} &= \sum_i \eta_L \beta_i \hat{P}_i + \sum_i \eta_i \left(\beta_i \hat{P}_i + \sum_{k \neq i} \beta_k \hat{P}_k \right) && (2.48)\\
&= \sum_i \eta_L \beta_i \hat{P}_i + \sum_i \eta_i \sum_j \beta_j \hat{P}_j && (2.49)\\
&= \left(\eta_L + \sum_i \eta_i \right) \sum_j \beta_j \hat{P}_j && (2.50)\\
&= \sum_i \beta_i \hat{P}_i && (2.51)
\end{aligned}$$

where the final equality follows from noting that $\eta_L + \sum_j \eta_j = 1$ by construction. Now examining the group of terms labeled $\mathcal{Y}$, first note that $\frac{\eta_i}{\theta_i} = \frac{P_i Y_i}{\sum_j P_j Y_j}$, which is industry i's share of total production value; call this share φ_i.

$$\begin{aligned}
\mathcal{Y} &= \sum_j \varphi_j \hat{P}_j - \sum_j \varphi_j \beta_j \hat{P}_j - \sum_j \varphi_j \sum_{k \neq j} \beta_k \hat{P}_k && (2.52)\\
&= \sum_j \varphi_j \hat{P}_j - \sum_j \varphi_j \sum_k \beta_k \hat{P}_k && (2.53)\\
&= \sum_j \varphi_j \hat{P}_j - \sum_k \beta_k \hat{P}_k, && (2.54)
\end{aligned}$$

where the final equality comes from the fact that $\sum_i \varphi_i = 1$. Finally, examine the group of terms labeled $\mathcal{Z}$. Note that

$$\sum_i \eta_i \frac{(1-\theta_i)}{\theta_i} = \sum_i \frac{R_i T_i}{m} \frac{w L_i}{P_i Y_i} \frac{P_i Y_i}{R_i T_i} = \frac{w}{m} \sum_i L_i = \eta_L. \tag{2.55}$$

Plugging this into the expression for $\mathcal{Z}$,

$$\begin{aligned}
\mathcal{Z} &= \left(\eta_L \left(\sum_i \lambda_i \frac{\sigma_i}{\theta_i} - 1 \right) + \eta_L \right) \frac{\hat{L}}{\sum_i \lambda_i \frac{\sigma_i}{\theta_i}} && (2.56)\\
&= \eta_L \hat{L} && (2.57)
\end{aligned}$$

Combining these results implies

$$\hat{m} = \eta_L \hat{L} + \sum_i \varphi_i \hat{P}_i \tag{2.58}$$

Change in Nontraded Good Production. For the nontraded good, regional production equals consumption, so $\hat{Y}_N^c = \hat{Y}_N^p$. Substitutions using (2.28), (2.29), (2.30), and (2.32) yield the following expression for the change in nontraded good output.

$$\hat{Y}_N^p = \frac{(1-\theta_N)}{\theta_N}\sigma_N\left(\hat{P}_N - \hat{w}\right) \tag{2.59}$$

$$= \frac{(1-\theta_N)}{\theta_N}\sigma_N\left(\hat{P}_N + \frac{\hat{L}}{\sum_i \lambda_i \frac{\sigma_i}{\theta_i}} - \sum_i \beta_i \hat{P}_i\right) \tag{2.60}$$

Combining Terms. Plugging (2.44), (2.58), and (2.60) into (2.43) for the nontraded industry N yields

$$\frac{(1-\theta_N)}{\theta_N}\sigma_N\left(\hat{P}_N + \frac{\hat{L}}{\sum_i \lambda_i \frac{\sigma_i}{\theta_i}} - \sum_i \beta_i \hat{P}_i\right) = \eta_L \hat{L} + \sum_i \varphi_i \hat{P}_i - \sigma \hat{P}_N + (\sigma-1)\sum_i \mu_i \hat{P}_i. \tag{2.61}$$

Isolate and collect terms including $\hat{P}_N$

$$\left[\frac{(1-\theta_N)}{\theta_N}\sigma_N(1-\beta_N) - \varphi_N + \sigma - (\sigma-1)\mu_N\right]\hat{P}_N = \left[\eta_L - \frac{(1-\theta_N)}{\theta_N}\frac{\sigma_N}{\sum_i \lambda_i \frac{\sigma_i}{\theta_i}}\right]\hat{L} + \sum_{i\neq N}\left[\frac{(1-\theta_N)}{\theta_N}\sigma_N\beta_i + \varphi_i + (\sigma-1)\mu_i\right]\hat{P}_i \tag{2.62}$$

Grouping terms on the left hand side and solving for $\hat{P}_N$,

$$\hat{P}_N = \frac{\eta_L - \frac{(1-\theta_N)}{\theta_N}\frac{\sigma_N}{\sum_i \lambda_i \frac{\sigma_i}{\theta_i}}}{\sum_{i'\neq N}\frac{(1-\theta_N)}{\theta_N}\sigma_N\beta_i' + \varphi_i' + (\sigma-1)\mu_i'}\hat{L} + \sum_{i\neq N}\xi_i \hat{P}_i \tag{2.63}$$

$$\text{where} \qquad \xi_i = \frac{\frac{(1-\theta_N)}{\theta_N}\sigma_N\beta_i + \varphi_i + (\sigma-1)\mu_i}{\sum_{i'\neq N}\frac{(1-\theta_N)}{\theta_N}\sigma_N\beta_{i'} + \varphi_{i'} + (\sigma-1)\mu_{i'}} \tag{2.64}$$

2.9.3 Restrictions to Drop the Nontraded Sector from Weighted Averages

Under Cobb-Douglas production with equal factor shares across industries ($\theta_i = \theta\ \forall i$), the first order conditions imply that, for all i

$$P_i(1-\theta)\frac{Y_i}{L_i} = w \tag{2.65}$$

$$\varphi_i(1-\theta) = \eta_L \lambda_i \tag{2.66}$$

$$\varphi_i = \left(\frac{\theta}{(1-\theta)}\eta_L \sum_{i'} \lambda_{i'} \frac{\sigma_{i'}}{\theta_{i'}}\right)\beta_i \tag{2.67}$$

$$\varphi_i = \kappa\beta_i, \tag{2.68}$$

where the final equality comes from defining κ as the coefficient on β_i, which does not vary across industries. Restrict consumer preferences to be Cobb-Douglas ($\sigma = 1$). Under this restriction, and plugging in (2.68), ξ_i is

$$\xi_i = \frac{\left(\frac{(1-\theta_N)}{\theta_N} + \kappa\right)\beta_i}{\sum_{i' \neq N}\left(\frac{(1-\theta_N)}{\theta_N} + \kappa\right)\beta_{i'}} \tag{2.69}$$

$$= \frac{\beta_i}{\sum_{i' \neq N}\beta_{i'}} \tag{2.70}$$

Plug this result into (2.3) and (2.1)

$$\hat{w} = \sum_{i \neq N}\beta_i \hat{P}_i + \beta_N\left(\frac{\sum_{i \neq N}\beta_i \hat{P}_i}{\sum_{i \neq N}\beta_i}\right) \tag{2.71}$$

$$= \left(1 + \frac{\beta_N}{1-\beta_N}\right)\sum_{i \neq N}\beta_i \hat{P}_i \tag{2.72}$$

$$= \frac{\sum_{i \neq N}\beta_i \hat{P}_i}{\sum_{i' \neq N}\beta_i'} \tag{2.73}$$

This is equivalent to omitting the nontraded industry N from the sums in (2.1) and (2.2).

2.10 Appendix B: Industry Aggregation

Begin with equation (2.7).

$$\hat{P}_{ig} = \mathbf{1}(ipc_{ig})(1 \hat{+} \tau_i) + \hat{P}^W_{ig}. \tag{2.74}$$

Plug this into (2.1), under the new notation including goods within industries.

$$\hat{w}_r = \sum_i \sum_{g \in i} \beta_{rig}(\mathbf{1}(ipc_{ig})(1 \hat{+} \tau_i) + \hat{P}^W_{ig}) \tag{2.75}$$

$$= \sum_i (1 \hat{+} \tau_i) \sum_{g \in i} \beta_{rig} \mathbf{1}(ipc_{ig}) + \sum_i \sum_{g \in i} \beta_{rig} \hat{P}^W_{ig} \tag{2.76}$$

The empirical analysis will impose the additional restriction of Cobb-Douglas production, as it is not feasible to calculate elasticities of factor substitution by industry and region. This restriction along with identical technologies across regions implies that $\sigma_{rig} = 1$ and $\theta_{rig} = \theta_i$. Imposing this restriction implies

$$\sum_{g \in i} \beta_{rig} \mathbf{1}(ipc_{ig}) = \frac{\frac{1}{\theta_i} \sum_{g \in i} L_{rig} \mathbf{1}(ipc_{ig})}{\sum_{i'} \frac{1}{\theta_{i'}} \sum_{g' \in i'} L_{ri'g'}} \tag{2.77}$$

$$= \frac{\frac{L_{ri}}{\theta_i} \frac{\sum_{g \in i} L_{rig} \mathbf{1}(ipc_{ig})}{L_{ri}}}{\sum_{i'} L_{ri'} \frac{1}{\theta_{i'}}} \tag{2.78}$$

$$= \beta_{ri} \phi_{ri} \tag{2.79}$$

$$\text{where} \qquad \phi_{ri} \equiv \sum_{g \in i} \frac{L_{rig}}{L_{ri}} \mathbf{1}(ipc_{ig}) \tag{2.80}$$

ϕ_{ri} is the fraction of industry i workers producing goods that face import competition. Now consider the second term in (2.76).

$$\sum_{g \in i} \beta_{rig} \hat{P}^W_{ig} = \frac{\frac{1}{\theta_i} \sum_{g \in i} L_{rig} \hat{P}^W_{ig}}{\sum_{i'} \frac{1}{\theta_{i'}} \sum_{g' \in i'} L_{ri'g'}} \tag{2.81}$$

$$= \frac{\frac{L_{ri}}{\theta_i} \frac{\sum_{g \in i} L_{rig} \hat{P}^W_{ig}}{L_{ri}}}{\sum_{i'}} \tag{2.82}$$

$$= \beta_{ri} \hat{P}^W_i \tag{2.83}$$

$$\text{where} \qquad \hat{P}^W_i \equiv \sum_{g \in i} \frac{L_{rig}}{L_{ri}} \hat{P}^W_{ig} \tag{2.84}$$

$\hat{P}^W_i$ is the average proportional change in prices in industry i, with weights based on the amount of labor producing each good in the industry. Although it is impossible to obtain world prices with this particular weighting scheme, it is likely that industry

level world prices calculated with a similar weighted mean structure will closely approximate this expression. Plugging these results back into (2.76), yields the result of the aggregation.

$$\hat{w}_r = \sum_i \beta_{ri}(\phi_{ri}(1 \hat{+} \tau_i) + \hat{P}_i^W) \tag{2.85}$$

2.11 Appendix C: Location Choice Estimation Equation Derivation

This appendix follows Scanlon et al. (2002) and Cadena (2007) to difference out time invariant unobservable terms from the location choice specification described in (2.21). The observed share of individuals in group g who choose to live in location d at time t, S_{gdt}, will consist of the true choice probability, π_{gdt}, and mean zero random sampling error, ξ_{gdt}.

$$S_{gdt} = \frac{e^{V_{gdt}}}{D_{gt}} + \xi_{gdt} \tag{2.86}$$

Taking logs yields

$$\ln S_{gdt} = ln(e^{V_{gdt}} + \xi_{gdt} D_{gt}) - \ln D_{gt}. \tag{2.87}$$

A first-order Taylor series approximation evaluated at $\xi_{gdt} = 0$ yields

$$\ln S_{gdt} \approx V_{gdt} - lnD_{gt} + \frac{\xi_{gdt}}{\pi_{gdt}}. \tag{2.88}$$

Plugging in the definition of V_{gdt} from (2.20),

$$\ln S_{gdt} \approx \alpha_g \ln w_{dt} + \mu_{gdt} + \eta_{gd} - lnD_{gt} + \frac{\xi_{gdt}}{\pi_{gdt}}. \tag{2.89}$$

The model is still nonlinear in α_g, due to its presence within D_{gt}. This term can be canceled by subtracting the log share of an arbitrary reference destination. For convenience, the reference state is h, the state of residence of individuals in group g.

$$\ln S_{gdt} - \ln S_{ght} \approx \alpha_g(\ln w_{dt} - \ln w_{ht}) + (\mu_{gdt} - \mu_{ght}) + (\eta_{gd} - \eta_{gh}) + \left(\frac{\xi_{gdt}}{\pi_{gdt}} - \frac{\xi_{ght}}{\pi_{ght}}\right) \tag{2.90}$$

Although the preceding expression is linear in α_g, it still contains unobserved components that may be correlated with log wages. The time invariant unobserved components, η_{gd}, can be canceled out by differencing over time.

$$d \ln S_{gd} - d \ln S_{gh} \approx \alpha_g (d \ln w_d - d \ln w_h) + \left[(d\mu_{gd} - d\mu_{gh}) + d\left(\frac{\xi_{gd}}{\pi_{gd}}\right) - d\left(\frac{\xi_{gh}}{\pi_{gh}}\right) \right] \tag{2.91}$$

2.12 Figures and Tables

Figure 2.1: Graphical Representation of Specific Factors Model of Regional Economies

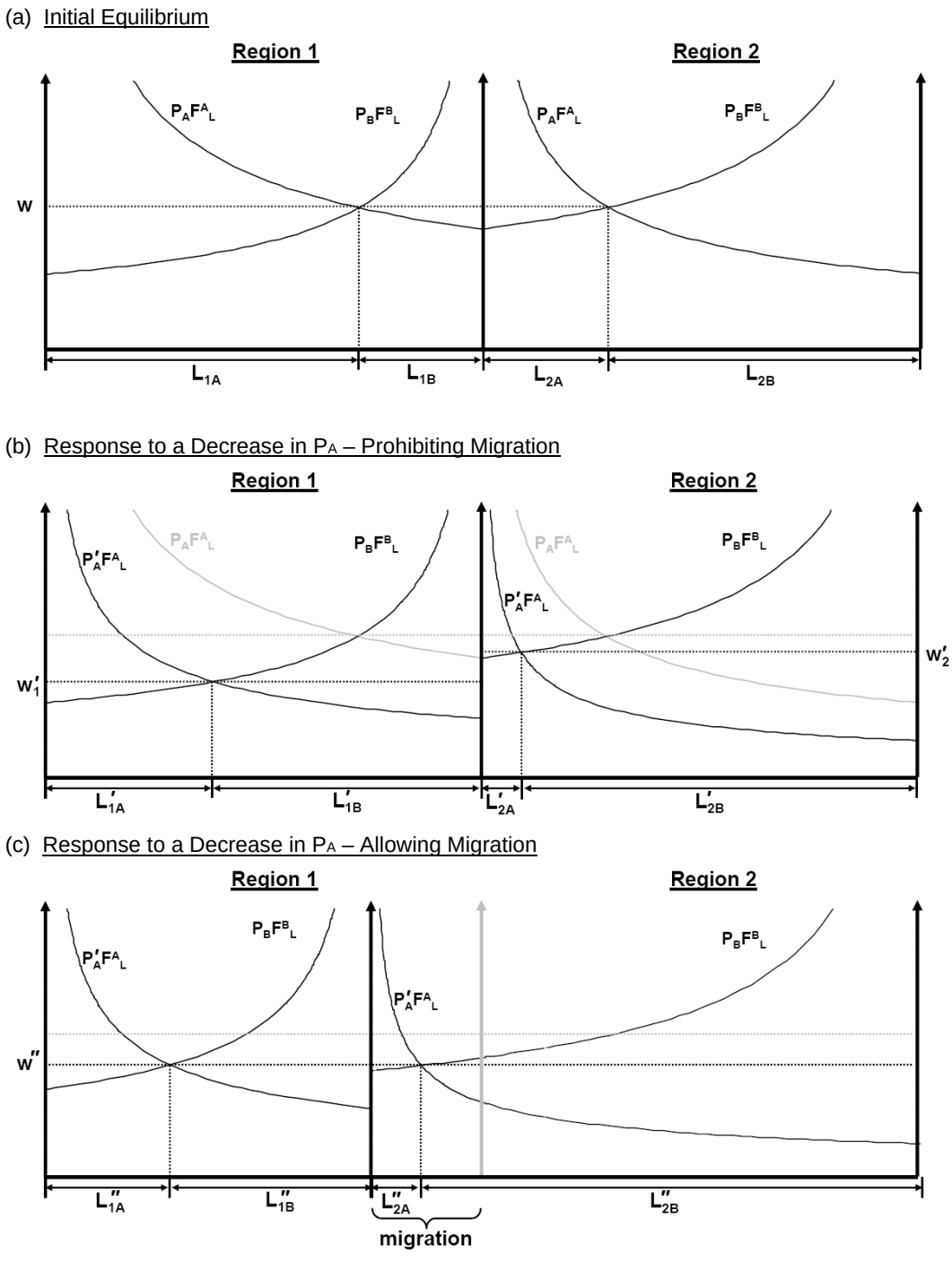
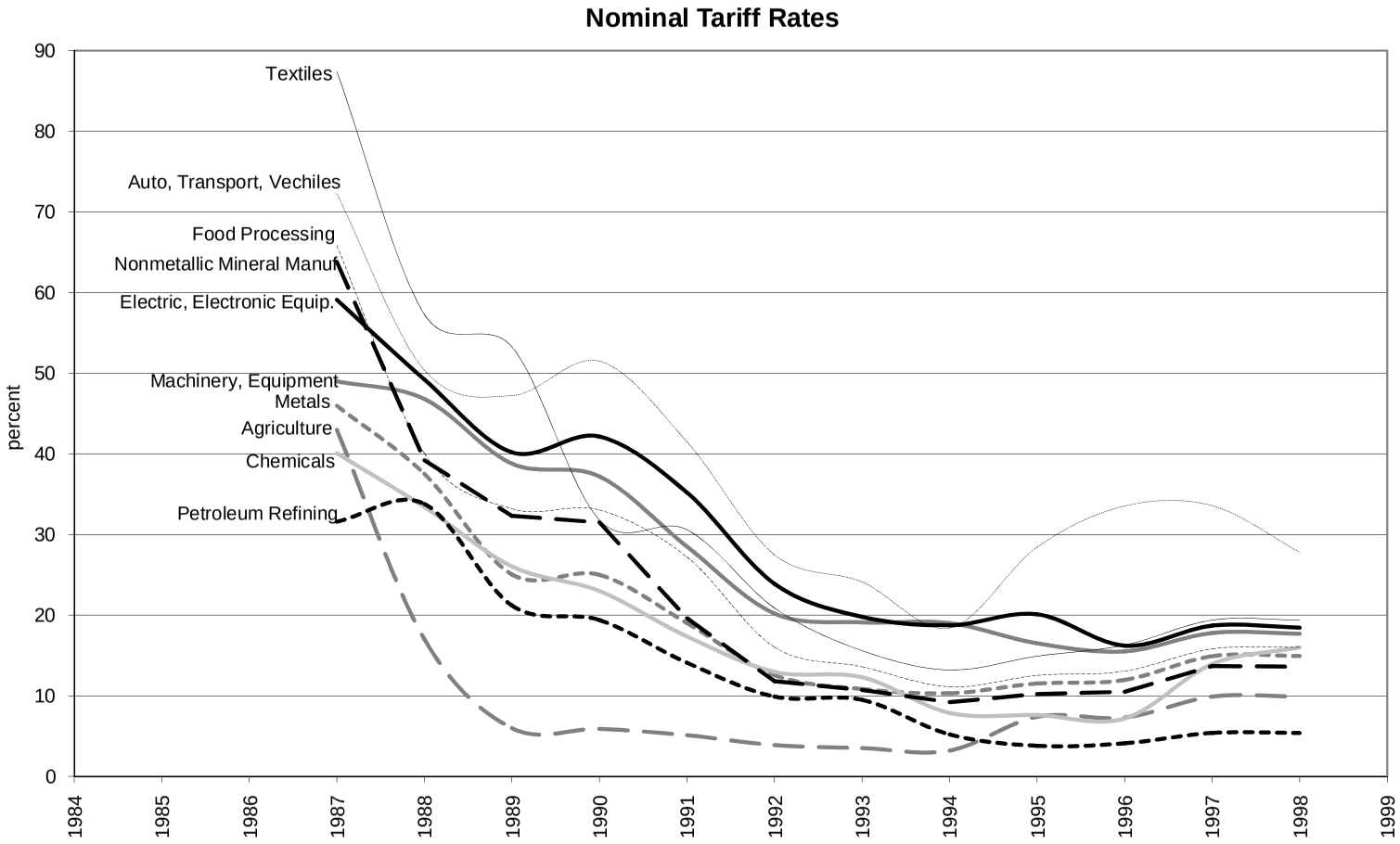
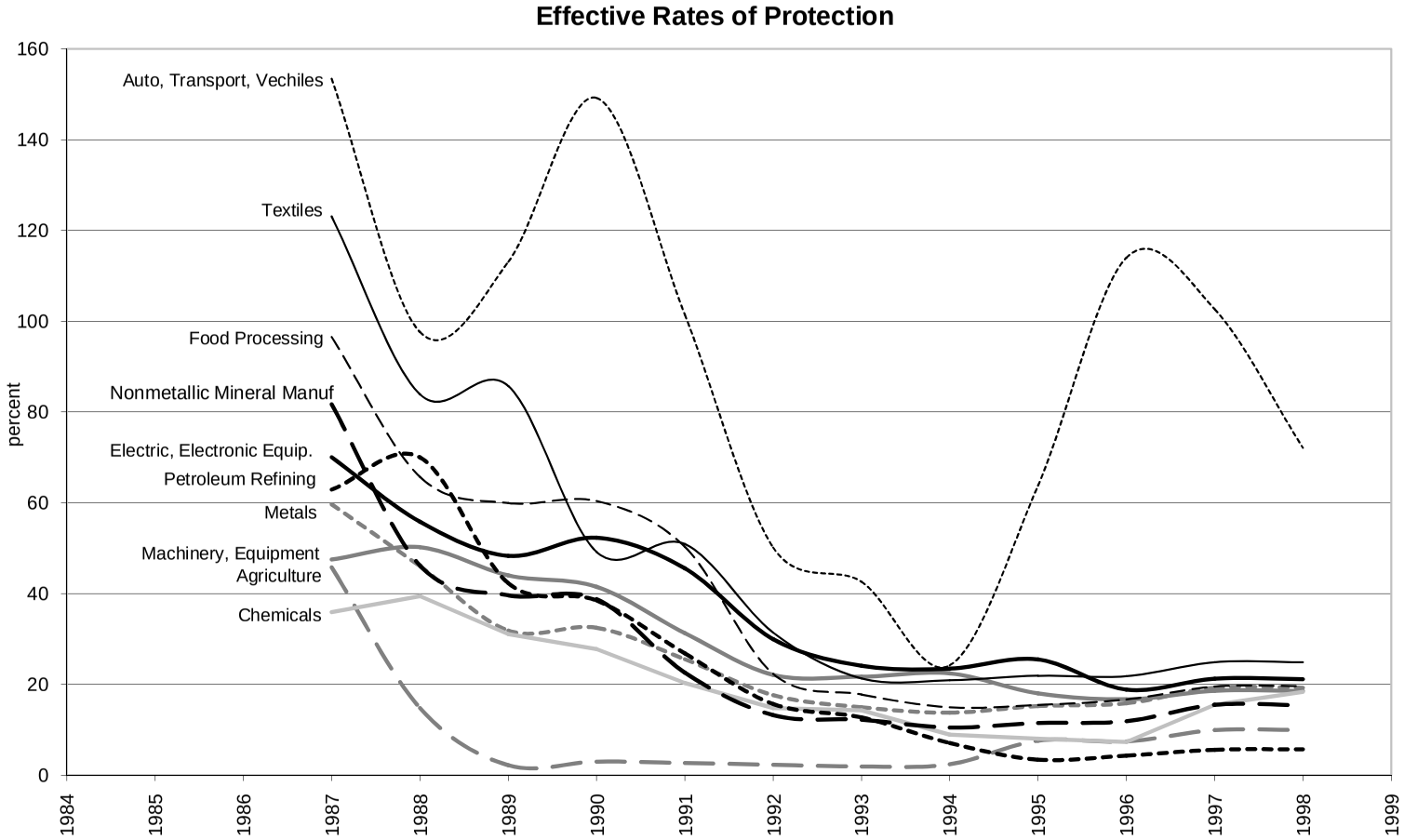


Figure 2.2: Nominal Tariff Timeline



Source: Nominal tariffs at the nivel 50 level come from Kume et al. (2003)
Nivel 50 tariffs were aggregated for matching to individual-level data using the concordance presented in IBGE (2004), weighted by value added.
The sectors presented are the ten largest based on value added in 1990

Figure 2.3: Effective Rate of Protection Timeline



Source: Effective rates of protection at the nivel 50 level come from Kume et al. (2003)
Nivel 50 ERP's were aggregated for matching to individual-level data using the concordance presented in IBGE (2004), weighted by value added.
The sectors presented are the ten largest based on value added in 1990

Figure 2.4: Industry Employment Growth and Tariff Changes

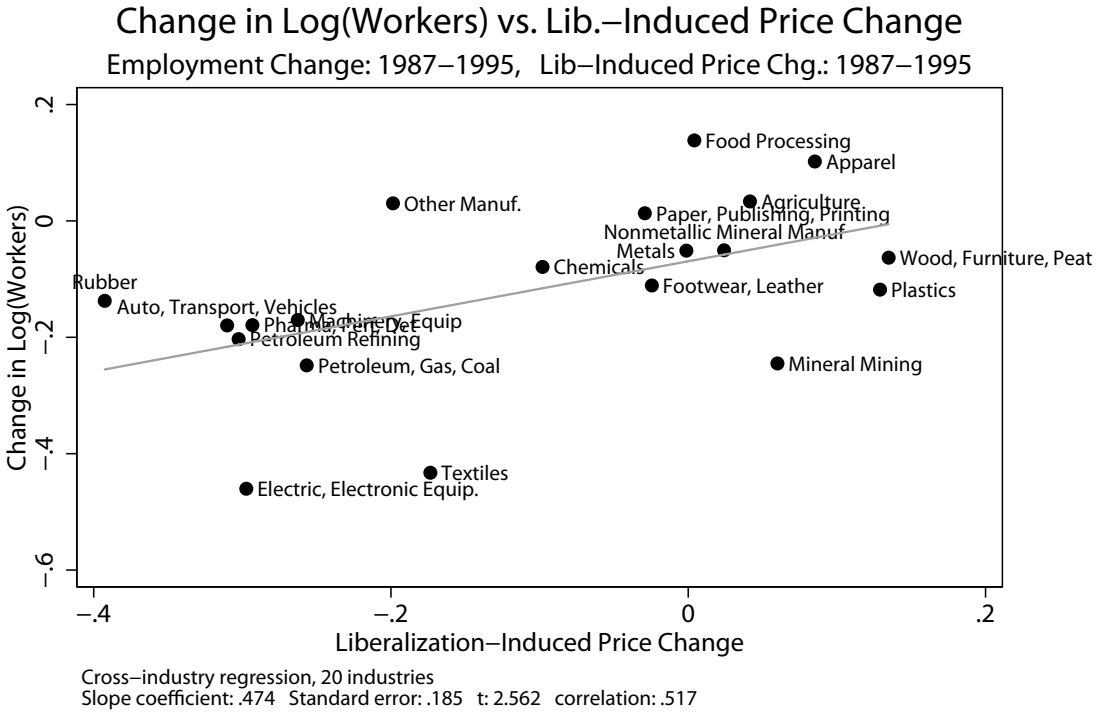


Figure 2.5: Industry Employment Growth and Tariff Changes - False Experiment

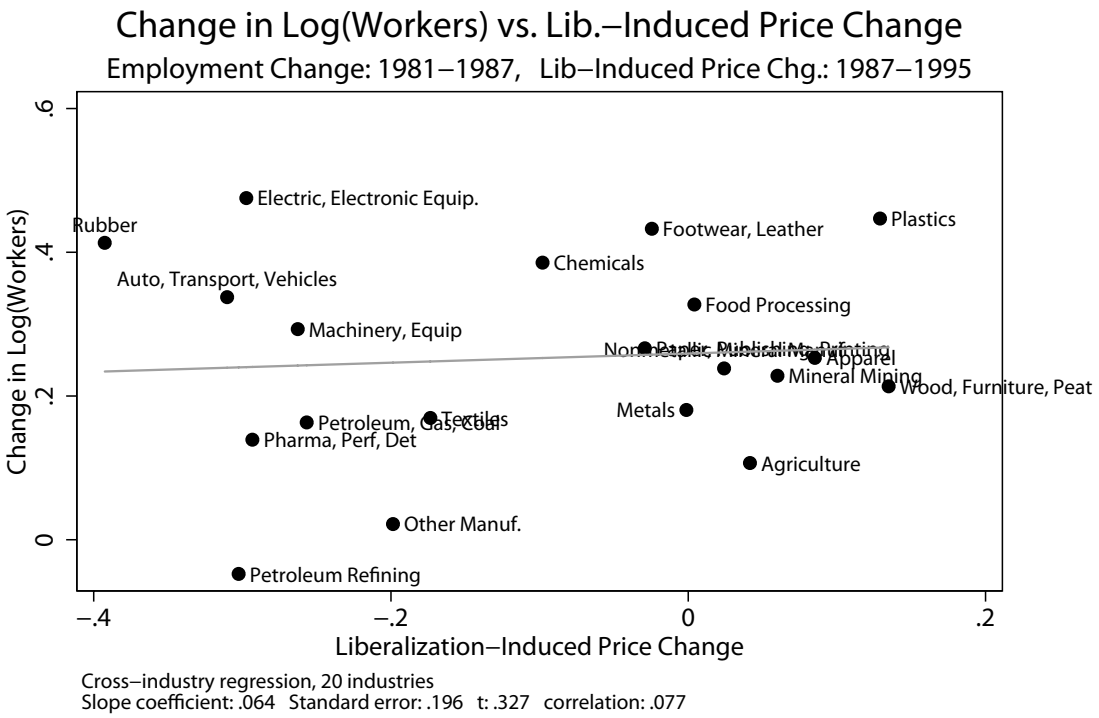


Figure 2.6: Relationship Between Tariff Changes and Pre-Liberalization Tariff Levels

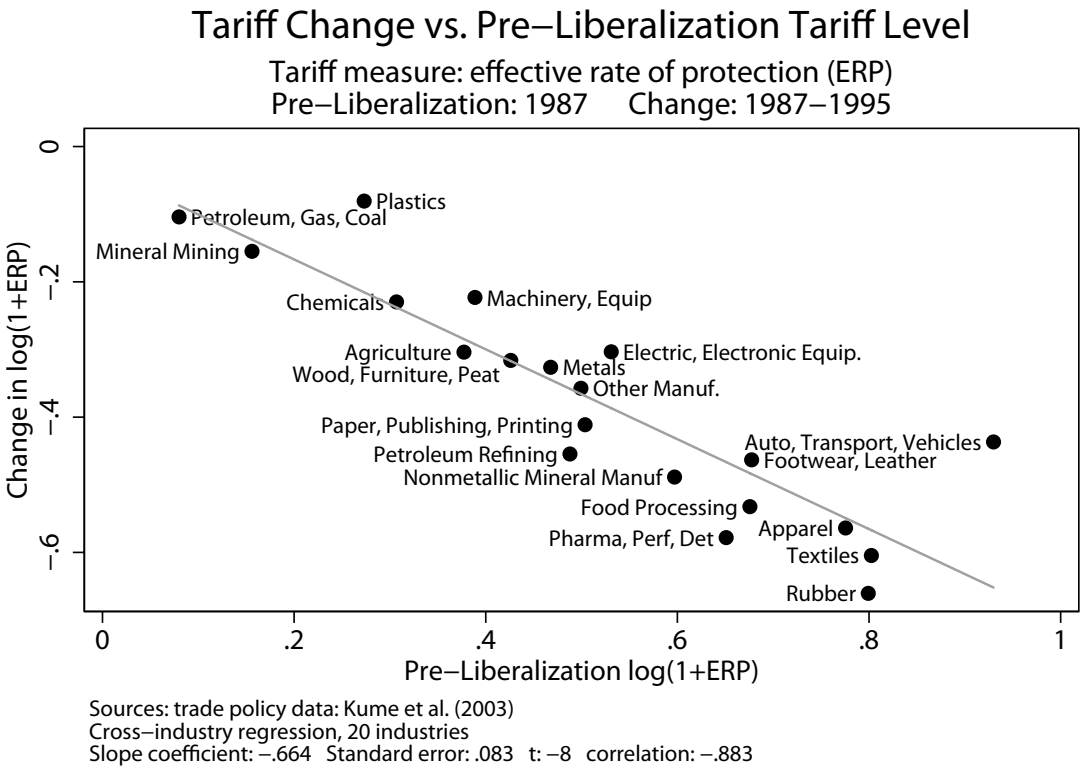
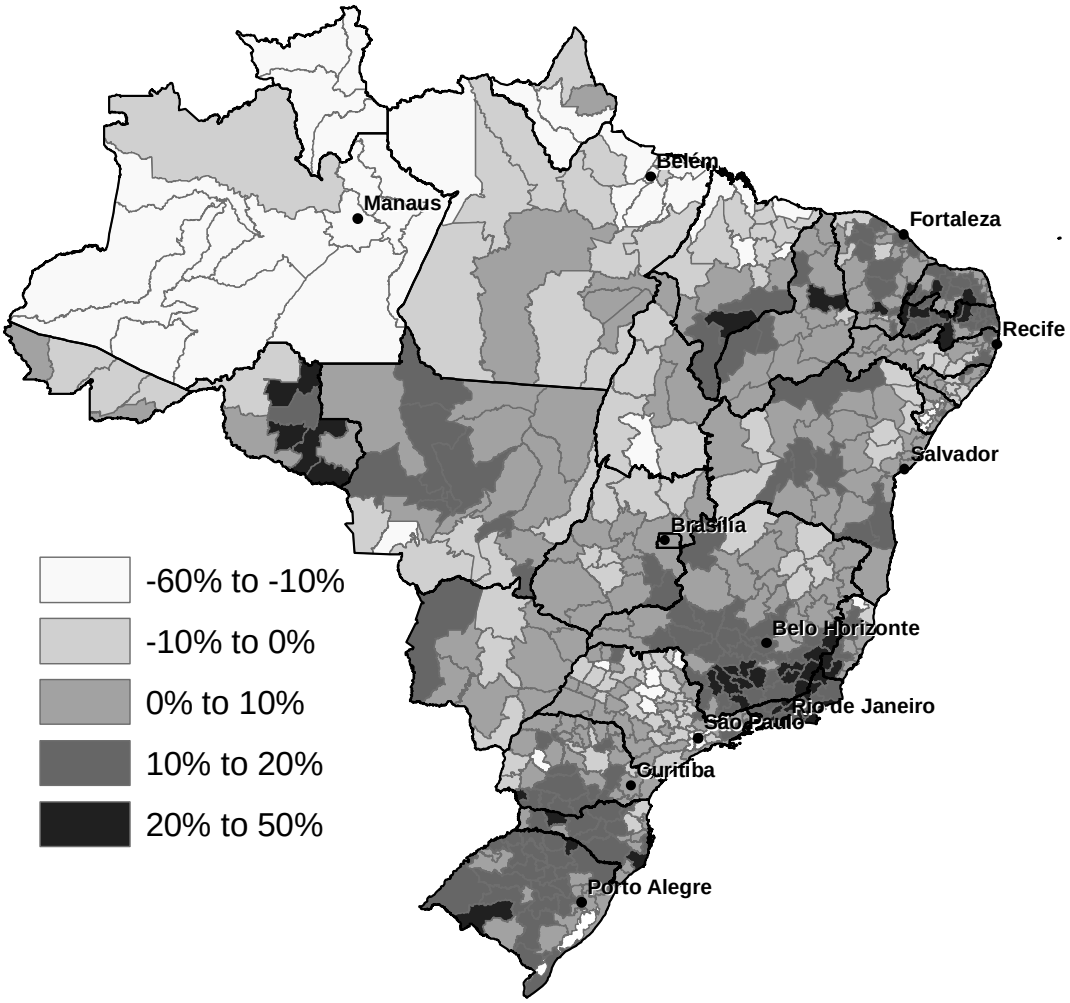
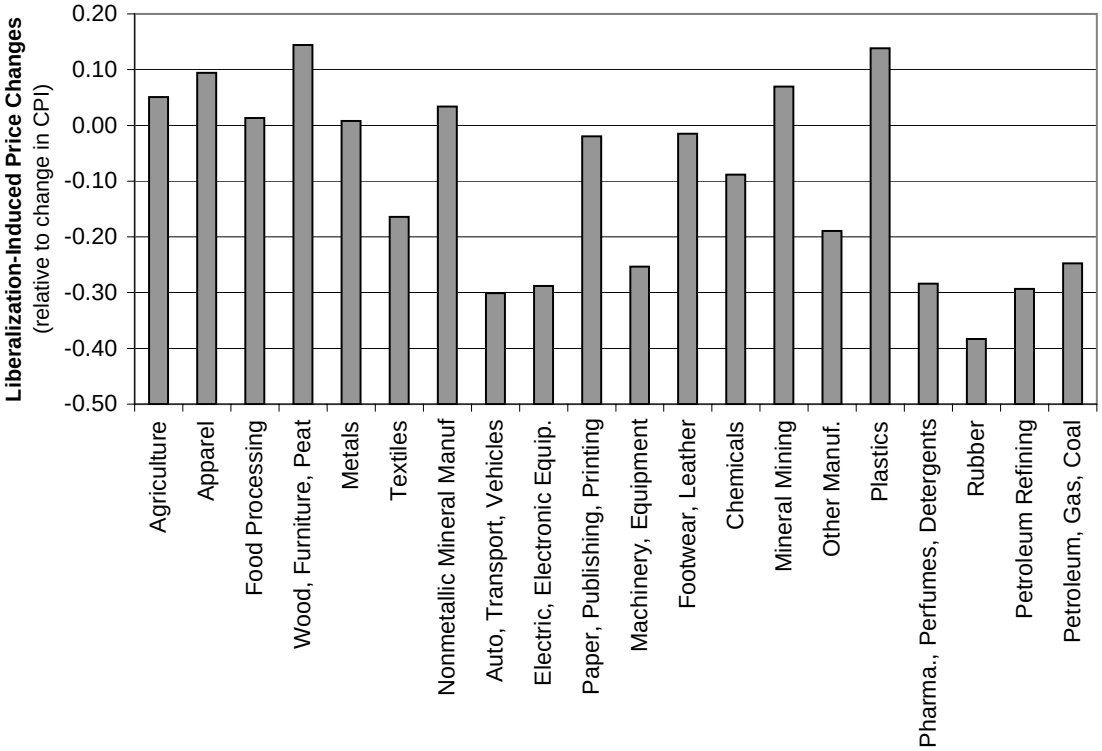


Figure 2.7: Regional Wage Changes



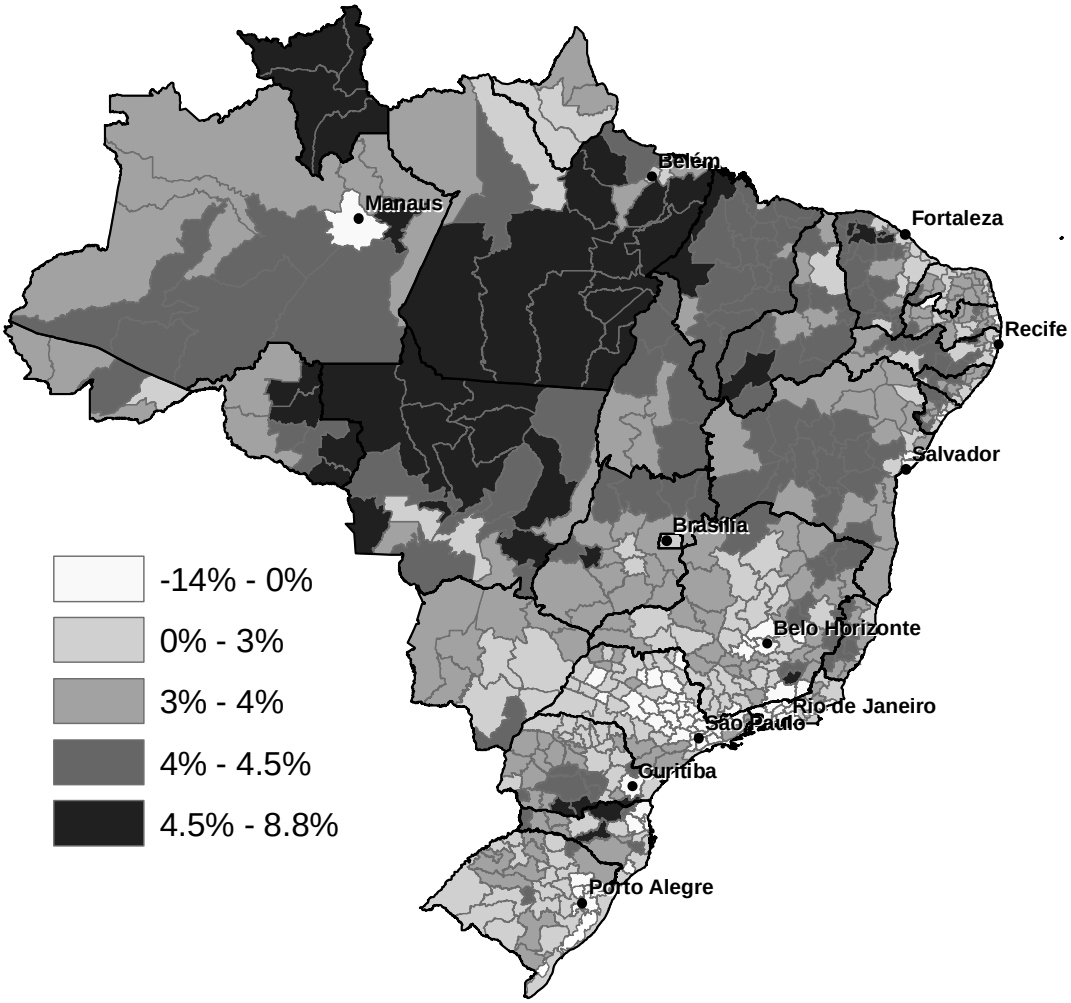
Proportional wage change by microregion - change in microregion fixed effects from wage regression

Figure 2.8: Tariff-Induced Price Changes



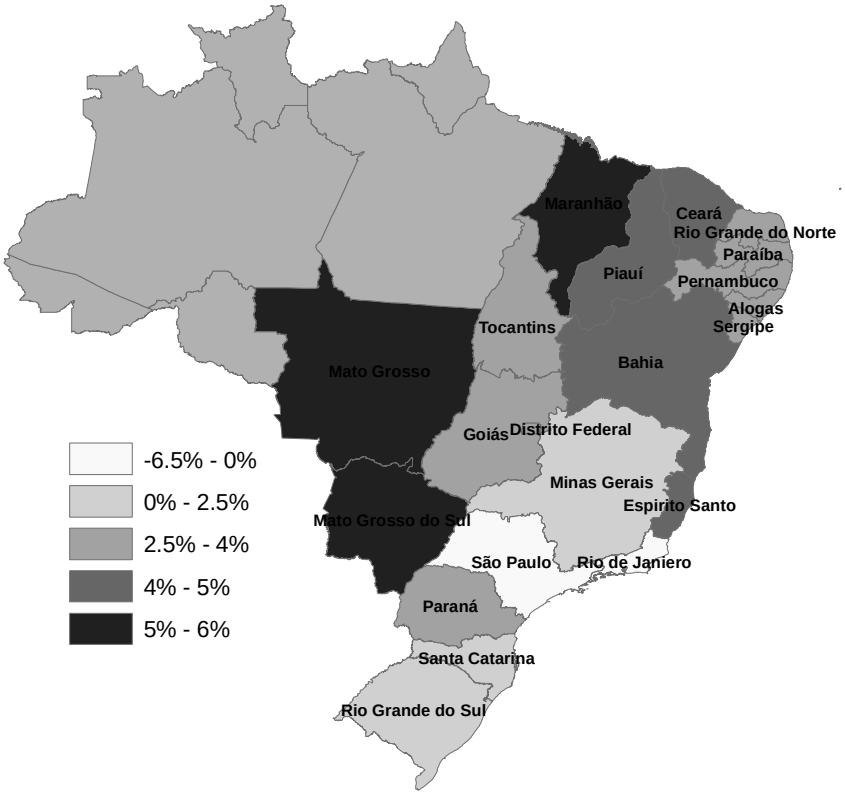
Source: Author's calculations - see text
Industries sorted by 1987 employment share (descending order)

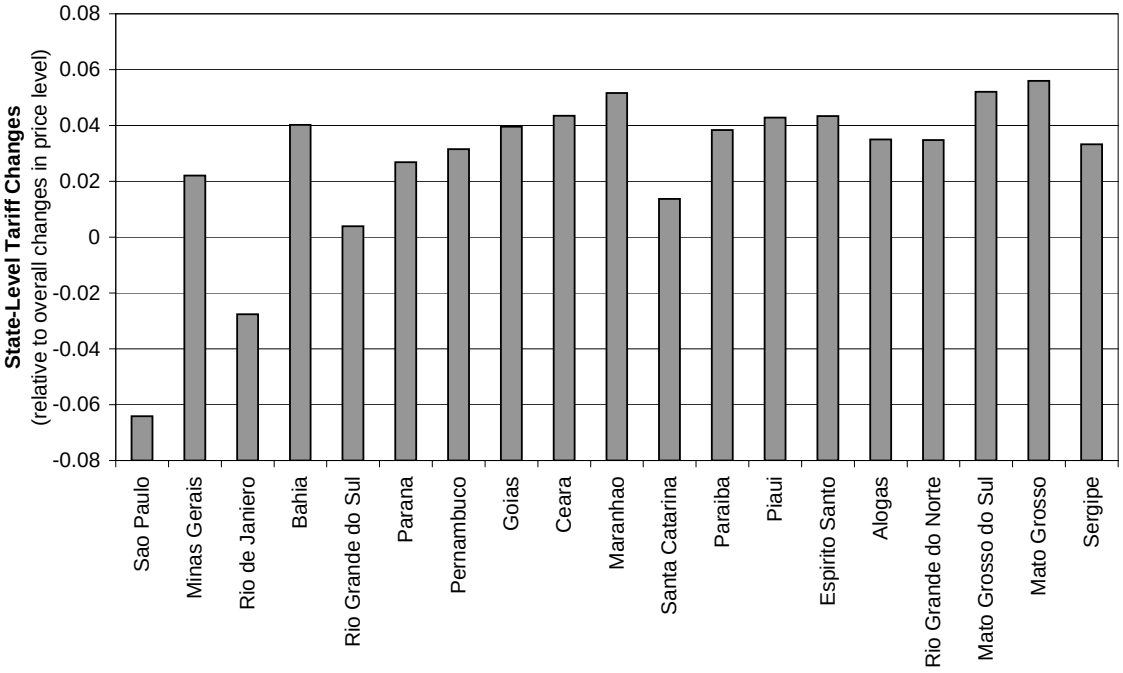
Figure 2.9: Region-Level Tariff Changes



Weighted average of proportional tariff changes - see text for details.

Figure 2.10: State-Level Tariff Changes





Weighted average of proportional tariff changes - see text for details.

Table 2.1: Industry Aggregation and Concordance

Final Industry	Sector Name	Nível 50	Nível 80	PNAD / 91 Census
1	Agriculture	1	101-199	011-037, 041, 042, 581
2	Mineral Mining (except combustibles)	2	201-202	050, 053-059
3	Petroleum and Gas Extraction and Coal Mining	3	301-302	051-052
4	Nonmetallic Mineral Goods Manufacturing	4	401	100
5	Iron and Steel, Nonferrous, and Other Metal Production and Processing	5-7	501-701	110
8	Machinery, Equipment, Commercial Installation Manufacturing, and Tractor Manufacturing	8	801-802	120
10	Electrical, Electronic, and Communication Equipment and Components Manufacturing	10-11	1001-1101	130
12	Automobile, Transportation, and Vehicle Parts Manufacturing	12-13	1201-1301	140
14	Wood Products, Furniture Manufacturing, and Peat Production	14	1401	150, 151, 160
15	Paper Manufacturing, Publishing, and Printing	15	1501	170, 290
16	Rubber Product Manufacturing	16	1601	180
17	Chemical Product Manufacturing	17,19	1701-1702, 1901-1903	200
18	Petroleum Refining and Petrochemical Manufacturing	18	1801-1806	201, 202, 352, 477
20	Pharmaceutical Products, Perfumes and Detergents Manufacturing	20	2001	210, 220
21	Plastics Products Manufacturing	21	2101	230
22	Textiles Manufacturing	22	2201-2205	240, 241
23	Apparel and Apparel Accessories Manufacturing	23	2301	250,532
24	Footwear and Leather and Hide Products Manufacturing	24	2401	190, 251
25	Food Processing (Coffee, Plant Products, Meat, Dairy, Sugar, Oils, Beverages, and Other)	25-31	2501-3102	260, 261, 270, 280
32	Miscellaneous Other Products Manufacturing	32	3201	300
99	Nontraded Goods and Services	33-43	3301-4301	340, 351-354, 410-424, 451-453, 461, 462, 464, 471-476, 481, 482, 511, 512, 521-525, 531, 533, 541-545, 551, 552, 571-578, 582-589, 610-619, 621-624, 631, 632, 711-717, 721-727, 901, 902

Table 2.2: Cross-Sectional Wage Regressions - 1991 and 2000 Census

dependent variable: log wage = ln((monthly earnings / 4.33) / weekly hours) at main job

Year	1991	2000
Age	0.060	0.067
	(0.000)**	(0.000)**
Age^2 / 1000	-0.616	-0.690
	(0.004)**	(0.003)**
Female	-0.364	-0.310
	(0.001)**	(0.001)**
Inner City	0.102	0.081
	(0.001)**	(0.001)**
Race		
Brown (parda)	-0.129	-0.124
	(0.001)**	(0.001)**
Black	-0.192	-0.164
	(0.002)**	(0.001)**
Asian	0.137	0.111
	(0.006)**	(0.005)**
Indigenous	-0.158	-0.102
	(0.010)**	(0.006)**
Married	0.190	0.161
	(0.001)**	(0.001)**
Fixed Effects		
Years of Education (18)	X	X
Industry (21)	X	X
Microregion (558)	X	X
Observations	4962311	5664677
R-squared	0.517	0.503

Robust standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%
Omitted category: unmarried white male with zero years of education, outside inner city, working in agriculture

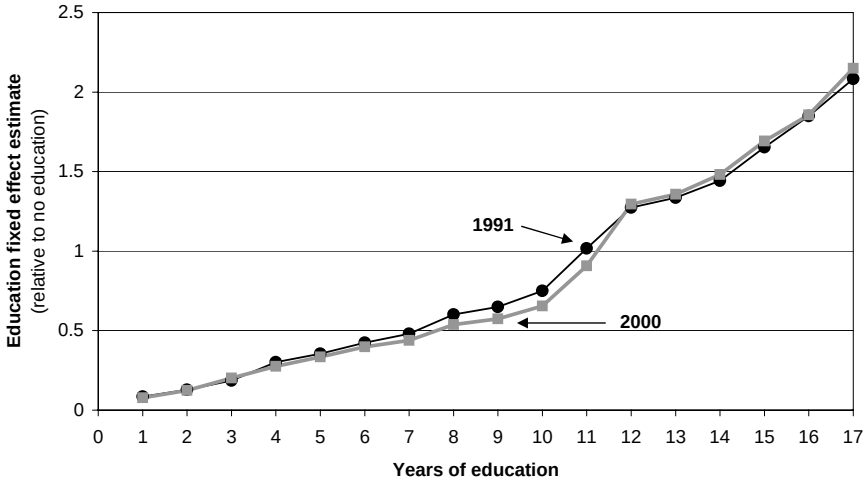


Table 2.3: The Effect of Tariff Changes on Price Changes

Effect of Tariff Changes on Price Changes 1987-1995

dependent variable: change in log wholesale price in Brazil

	(1)	(2)	(3)	(4)
$\Delta \ln(1 + \tau_i)$	0.029	0.142		
	(0.512)	(0.491)		
$\gamma i \, \Delta \ln(1 + \tau_i)$			12.587	12.240
			(5.446)*	(6.117)$^{+}$
$\Delta \ln P_{US,i}$		0.694		0.397
		(1.014)		(0.849)
Constant	18.686	18.603	18.933	18.855
	(0.260)**	(0.327)**	(0.159)**	(0.295)**
R-squared	0.000	0.036	0.281	0.293

Robust standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%
20 industry observations
weighted by 1990 industry value added

Table 2.4: The Effect of Liberalization on Local Wages

dependent variable: change in log microregion wage[a]

	(1)	(2)
Regional Liberalization Shock	0.764	0.629
	(0.242)**	(0.171)**
	[0.381]$^{+}$	[0.158]**
Constant	0.037	
	(0.007)**	
	[0.022]	
State Fixed Effects (27)		X
R-squared	0.061	0.620

Heteroskedasticity robust standard errors in parentheses ( )
Standard errors adjusted for 27 clusters by state in brackets [ ]
+ significant at 10%; * significant at 5%; ** significant at 1%
558 microregion observations
Weighted by inverse of standard error of microregion wage premium estimate
[a] Change in microregion wage premium, calculated from microregion fixed effects in cross-sectional wage regressions

Table 2.5: Migration Summary Statistics

Demographic Group	Fraction of Total Population in Demographic Group	Fraction of Demographic Group that Ever Migrated	Migrated in the 10 Years Preceding the Survey	Migrated during Sept 1982 - Sept 1988 (Pre-Liberalization)	Migrated during Sept 1996 - Sept 2002 (Post-Liberalization)
All	100.00%	29.04%	9.65%	6.22%	5.90%
Gender					
Female	51.54%	28.46%	9.21%	5.94%	5.66%
Male	48.46%	29.65%	10.12%	6.51%	6.15%
Age					
18-24	24.93%	19.83%	10.58%	5.63%	7.19%
25-34	30.27%	28.36%	12.43%	8.09%	7.65%
35-54	44.80%	34.63%	7.26%	5.15%	4.11%
Education					
0	11.72%	30.06%	8.80%	5.39%	5.57%
1-3	14.51%	31.01%	9.82%	6.31%	5.99%
4-7	31.46%	29.92%	9.90%	6.32%	5.91%
8-10	16.30%	27.58%	9.76%	6.28%	5.76%
11-14	20.00%	25.81%	9.06%	6.14%	5.73%
15+	2.22%	36.99%	14.05%	10.02%	9.10%
Race					
White	55.50%	28.85%	9.22%	6.30%	5.51%
Brown (*Pardo*)	38.16%	30.09%	10.65%	6.49%	6.51%
Black	5.72%	23.41%	6.95%	3.71%	4.83%
Asian	0.48%	33.81%	12.63%	4.97%	10.39%
Indigenous	0.14%	30.34%	10.55%	3.23%	10.77%
Marital Status					
Married	62.23%	32.46%	10.13%	6.88%	5.89%
Unmarried	37.77%	23.40%	8.87%	5.04%	5.91%
Family Size					
1-2	15.51%	31.31%	11.95%	7.14%	7.87%
3-4	49.84%	28.93%	9.58%	6.45%	5.67%
5-6	25.89%	29.32%	8.98%	5.97%	5.16%
7+	8.76%	24.80%	8.00%	4.93%	4.90%
Baseline Population	81,099,568	81,099,568	81,099,568	72,282,488	92,562,936
Survey Years Utilized	1992-2002	1992-2002	1992-2002	1992	2002
Observations	1,612,368	1,612,368	1,612,368	158,061	208,080

Source: Author's calculations based on 1992-2002 PNAD
Sample: Individuals age 18-55

Table 2.6: The Effect of State-Level Tariff Changes on Location Choice

Additional grouping beyond source state	Homogeneous effect across groups	Heterogeneous effect across groups	Observations
None	1.920		168
	(0.983)+		
Age	1.848		253
	(0.872)*		
Age 18-34		2.524	
		(0.864)**	
Age 35-55		0.576	
		(1.725)	
Gender	1.768		258
	(0.975)+		
Male		2.118	
		(1.072)+	
Female		1.381	
		(0.898)	
Education	2.733		251
	(1.048)*		
0-7 Years		3.583	
		(1.006)**	
8+ Years		1.048	
		(1.335)	
Race	1.828		241
	(1.029)+		
White		2.376	
		(1.348)+	
Non-white		1.054	
		(0.844)	
Familiy Size	2.291		231
	(1.119)+		
4 or fewer		2.413	
		(1.043)*	
5 or more		2.061	
		(1.369)	

Standard errors clustered by 19 destination states
+ statistically significant at 10%, * at 5%, ** at 1%

Observations represent group (including source state) x destination pairs
Sample: Individuals age 18-55 at time of survey
Dropping groups with less than 5 observations in either period
Weighted by the square root of the number of observations in each cell

Source: Author's calculations based upon the following data sets
Migration and employment: 1987,1992, and 2002 PNAD
Trade policy: Kume et al. (2003)
Import penetration: IBGE Brazil national accounts

Table 2.7: Liberalization-Induced Population Shifts

State	Liberalization-induced population change	1988 population (aged 18-55)	Proportional population change
Mato Grosso	20,655	780,113	2.65%
Mato Grosso do Sul	19,820	853,602	2.32%
Paraiba	18,420	1,347,519	1.37%
Espirito Santo	13,553	1,161,370	1.17%
Alogas	10,877	987,854	1.10%
Bahia	53,789	4,936,731	1.09%
Pernambuco	33,794	3,209,443	1.05%
Ceara	27,433	2,703,695	1.01%
Parana	40,412	4,375,543	0.92%
Piaui	8,541	1,051,501	0.81%
Minas Gerais	58,643	7,481,558	0.78%
Sergipe	4,141	580,131	0.71%
Rio Grande do Norte	6,453	1,016,421	0.63%
Goias	17,062	3,244,584	0.53%
Maranhao	9,111	2,007,522	0.45%
Santa Catarina	3,236	2,197,374	0.15%
Rio Grande do Sul	-4,749	4,672,987	-0.10%
Rio de Janiero	-43,956	7,331,464	-0.60%
Sao Paulo	-297,234	16,810,570	-1.77%

Source: Author's calculations - see text for details

CHAPTER III

Overestimating the Effect of Complementarity on Skill Demand

3.1 Introduction

Numerous studies have documented substantial increases in U.S. wage inequality beginning in the early 1980's.[1] A large number of these analyses estimate cost function parameters in an effort to measure the effect of capital-skill complementarity on increased skill demand. In this paper, I present a model of production incorporating capital-skill complementarity showing that cost minimizing behavior will lead these previous studies to overestimate the effect of complementarity when production is subject to skill-biased technological change. I then implement a novel instrumental variables strategy based on changes in the tax treatment of income from capital during the early 1980's to show that the standard complementarity estimates are biased upward in practice.

Cost function estimates with quasi-fixed capital were first introduced in the inequality literature by Berman, Bound and Griliches (1994), and a large number of subsequent papers utilize this approach.[2] The following intuition explains why estimates derived using this approach will be systematically biased toward overes-

[1] Recent surveys of the large wage inequality literature include Acemoglu (2002) and Card and DiNardo (2005).

[2] Examples include Autor, Katz and Krueger (1998); Berman and Machin (2000); Berman, Somanathan and Tan (2005); Blonigen and Slaughter (2001); Caroli and van Reenen (2001); Chun (2003); Doms, Dunne and Troske (1997); Dunne, Haltiwanger and Troske (1997); Goldin and Katz (1998); Haskel and Slaughter (2002); Machin and Van Reenen (1998); and Pavcnik (2003).

timating the impact of capital-skill complementarity. The cost-function approach derives an estimating equation that relates changes in skill demand to changes in capital, with the regression coefficient on capital representing complementarity. The equation's error term represents skill-biased technological change (SBTC) in production. Firms experiencing SBTC will by definition increase their skill demand, but if complementarity is present, the increased use of skilled labor will also lead the firm to increase capital usage. Optimal firm behavior in the presence of complementarity implies a positive relationship between SBTC (the error term) and capital changes (the regressor of interest). Thus, the estimated coefficient on capital changes will be biased upward, overstating the impact of capital-skilled complementarity on skill demand.

After demonstrating this intuition in a production framework that incorporates capital-skill complementarity, the analysis moves to determining the practical importance of the bias. I introduce a novel instrumental variable derived from policy changes in the tax treatment of capital that generated variation in the user cost of capital faced by different industries. This approach is particularly well suited to identifying the role of complementarity, since it relies on exogenous variation in the price of capital across industries. The empirical results show that the theoretically predicted bias is realized in practice. The OLS estimates overstate the importance of capital-skill complementarity relative to the IV estimates, which are indistinguishable from zero, indicating no significant role of complementarity.

Previous papers in the wage inequality and complementarity literatures have noted the possibility of biased cost function estimates resulting from measurement error or endogeneity of cost function inputs. Dunne et al. (1997) and Duffy, Papageorgiou and Perez-Sebastian (2004) respond to these concerns by using lagged values of pro-

duction inputs and output as instrumental variables.[3] Krusell, Ohanian, Rios-Rull and Violante (2000) utilize functional form restrictions and nonlinear estimation techniques to resolve potential endogeneity when estimating the effects of complementarity in the presence of skill-biased technological change.

The present analysis contributes to the previous literature in two ways. First, it refines the general endogeneity concerns discussed previously, demonstrating in a simple production model that optimal firm behavior itself will generate bias in a particular direction, overstating the role of complementarity. This bias is neither arbitrary, nor the result of measurement error, but results directly from cost minimizing behavior. Second, this paper uses a new policy-driven instrumental variables approach to consistently identify the effect of complementarity on changes in skill demand. This represents an alternative to the lagged-values instruments and simulation estimation approaches employed previously.

The analysis presented here has implications beyond the inequality literature. In general, OLS estimates of cost function parameters will be systematically biased when the following two conditions hold: 1) production is modeled with a quasi-fixed factor that exhibits different levels of substitutability across variable inputs, and 2) the production function is subject to factor-biased technical change. These conditions clearly hold in the inequality literature, but they are also likely to be relevant in industry studies of productivity growth that utilize the quasi-fixed factor assumption. Caves, Christensen and Swanson (1981) introduced the quasi-fixed factor technique in the productivity growth context, and more recent studies utilizing similar techniques include Bloch and Tang (2007), Casarin (2006), Lee (2008), and Nostbakken (2006). Understanding the extent of capital-skill complementarity in production is

[3] Although Dunne et al. utilize different instruments, their long-difference IV cost function estimates also support this paper's conclusion. The IV analysis in Duffy et al. (2004) yields very imprecise estimates, making it difficult to infer bias by comparison with baseline estimates.

also of independent interest. This parameter is fundamental to the study of labor demand, particularly in measuring the elasticity of substitution between different types of labor. Such labor-labor elasticities are necessary to understand how changes in workforce skill mix affect relatives wages (Fallon and Layard 1975) and in deciding how to aggregate different groups of workers when conducting empirical work. Capital-skill complementarity estimates are also of direct interest when predicting the effect of capital subsidies on different workers' wages (Hamermesh 1993).

This paper has four remaining sections. The next section describes how cost function estimation has been employed in the wage inequality literature and discusses the source of estimation bias. Section 3.3 presents a model that explicitly incorporates capital-skill complementarity, demonstrating that the standard estimation procedure will overestimate the effect of complementarity. Section 3.4 implements an instrumental variables strategy suggesting that the theoretically predicted bias is present in practice, and section 3.5 concludes.

3.2 The Complementarity / SBTC Decomposition

Two potential causes of increased demand for skilled labor relative to unskilled labor are skill-biased technological change (SBTC) and capital-skill complementarity. SBTC is normally defined in a two-factor model, including skilled and unskilled labor. Berman, Bound and Machin (1998) provide a concise definition: "A skill-biased technological change is an exogenous change in the production function that increases the [relative demand for skilled to unskilled labor] at the current wage level." An alternative driver of within-industry increases in relative skill demand is capital-skill complementarity combined with falling capital prices. A production function exhibits capital-skill complementarity if its derived factor demands imply that capital

is more complementary with skilled labor than with unskilled labor. Under capital-skill complementarity, a fall in the price of capital will result in an increase in the demand for skilled labor relative to unskilled labor, given fixed relative wages. As shown in Figure 3.1, the price of new investment relative to production worker wages fell sharply during the first half of the 1980's, the time period exhibiting the sharpest increase in inequality (Card and DiNardo 2002).

Thus, both SBTC and capital-skill complementarity may have driven shifts in relative skill demand giving rise to increased inequality. Given the fundamental difficulty in directly measuring technological changes, studies generally seek to measure the effect of capital-skill complementarity and attribute residual shifts in relative skill demand to SBTC. In an effort to generate such an estimate of the effect of capital-skill complementarity on inequality, Berman, Bound and Griliches (1993, 1994), hereafter BBG, adapt a technique from Brown and Christensen (1981). They estimate an industry-level cost function using data on U.S. industries from the Annual Survey of Manufactures, and use the resulting parameter estimates to describe the effect of capital-skill complementarity on changes in industry skill share. The remainder of this section describes the BBG cost function estimation approach in order to highlight potential problems in the approach's ability to identify the effect of complementarity on skill share.

An estimation equation that distinguishes between the effects of capital-skill complementarity and SBTC can be derived from a translog variable cost function of the

form

$$\begin{aligned}\ln VC =& \alpha_0 + \alpha_y \ln Y + \sum_j \alpha_j \ln w_j + \beta \ln K + \frac{1}{2}\gamma_{YY}(\ln Y)^2 \\ &+ \frac{1}{2}\sum_j \sum_k \gamma_{jk} \ln w_j \ln w_k + \frac{1}{2}\delta(\ln K)^2 + \sum_j \rho_{Y_j} \ln Y \ln w_j \\ &+ \sum_j \rho_j \ln w_j \ln K + \pi \ln Y \ln K + \phi_t t + \frac{1}{2}\phi_{tt} t^2 + \phi_{tY} t \ln Y \\ &+ \sum_j \phi_{tw_j} t \ln w_j + \phi_{tK} t \ln K\end{aligned} \tag{3.1}$$

where VC is variable cost, Y is value added, w_j is the cost of variable input j, K is capital, and t is time, representing technical change. BBG assume that capital is quasi-fixed, implying that firms do not maximize over capital, which accounts for its inclusion separate from other variable inputs in (3.1). Under this assumption, cost minimization yields a share equation which is then time differenced to yield

$$dS_j = \phi_{tw_j} dt + \rho_{Y_j} d\ln Y + \sum_k \gamma_{jk} d\ln w_k + \rho_j d\ln K \tag{3.2}$$

where S_j is the wagebill share of variable input j, and d is the long difference operator. Assuming linear homogeneity of the cost function, constant returns to scale production, and that all industries have the same elasticities of substitution between factors yields the following estimating equation for industry i:

$$dS_{S,i} = \gamma d\ln(w_{S,i}/w_{U,i}) + \rho d\ln(K_i/Y_i) + \phi_i dt \tag{3.3}$$

where $S_{S,i}$ is the wagebill share of skilled workers, $w_{S,i}$ is the wage of skilled workers, and $w_{U,i}$ is the wage of unskilled workers in industry i. γ is related to σ_{SU}, the elasticity of substitution between skilled and unskilled labor, and ρ measures the effect of capital-skill complementarity on increases in demand for skilled labor relative to unskilled labor. The technology term in this equation, $\phi_i dt$, includes an industry subscript, which can be interpreted as modeling a common cross-industry technology

shock that has different effects on each industry.[4] In what follows, (3.3) will be referred to as the "decomposition equation."

In practice, the technology term in the decomposition equation, $\phi_i dt$, is interpreted as the error term of the estimating regression. (3.3) is generally estimated using industry or firm level data that is differenced over time spans ranging from 1 to 14 years. When determining how much of the changes in skill share can be attributed to capital-skill complementarity, one is primarily interested in estimating the parameter ρ in (3.3), which is identified by cross-industry variation in the change in capital intensity. By imposing the quasi-fixed capital assumption, the analysis assumes that changes in capital intensity are not the result of decisions by maximizing agents, and thus are exogenous to technology shocks in the error term.

Under the quasi-fixed capital assumption agents do not adjust capital, but the analysis simultaneously relies on capital intensity changes to identify the parameter of interest. Moreover, capital investment data almost certainly reflect the decisions of cost minimizing firms to some degree, so investment decisions are likely to be affected by changes in technology. Therefore, changes in capital intensity will be correlated with technology shocks in the error term, resulting in a biased estimate of the causal effect of complementarity on changes in skill share.[5]

The same problem can be seen from another perspective when considering the potential sources of identifying cross-industry variation in capital intensity changes. The two most likely sources of variation are different capital price changes across industries and different arrival times of new technology to different industries. Since

[4] An observationally equivalent interpretation would impose a common effect of a given technology shock in all industries, but would allow for different shocks in each industry.

[5] Situations in which (3.3) is estimated using one-year differences may not suffer as much from this problem, as capital intensity may not have time to adjust to recent technology shocks over such a short time span. However, if technology shocks are serially correlated within industries, then the change in capital intensity in a given year, which is driven by the previous year's shock, will still be correlated with the error term, leading to bias. Since industries receiving new technologies are likely to experience the continued influence of technological developments, such serial correlation is quite likely in this case.

capital-skill complementarity implies that industries experiencing a decrease in the price of capital will increase their skill share, identification based on different capital price changes will be successful. Identification based on different arrival times of technology is more problematic. Variation in the error term is interpreted as resulting from skill-biased changes in technology. Industries experiencing large skill-biased technology shocks by definition will have more positive changes in skill share conditional on the change in capital intensity. If industry production functions exhibit complementarity, then increases in skill-share will raise the marginal product of capital and induce increased investment. Therefore, complementarity creates a causal link between SBTC and changes in capital intensity, which results in an overestimate of the effect of complementarity.

3.3 The Decomposition in a Model with Complementarity

In order to demonstrate the preceding intuition, this section presents a framework that explicitly imposes capital-skill complementarity (rather than simply allowing for complementarity as with the translog cost function). This framework demonstrates the resulting association between SBTC (the error term in (3.3)) and changes in capital intensity (the regressor of interest in (3.3)).

As defined by Griliches (1969), capital-skill complementarity implies that

$$\sigma_{KU} > \sigma_{KS} \tag{3.4}$$

where σ_{ij} is the Allen-Uzawa partial elasticity of substitution between factors i and j, and U, S, and K represent unskilled labor, skilled labor, and capital, respectively. The simplest three-factor production function that allows the imposition of capital-skill complementarity as defined in (3.4) is the two-level CES production function

examined by Sato (1967):[6]

$$Y = [\alpha Z^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(g_U L_U)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}$$
$$\text{where } Z = [\beta(g_K K)^{\frac{\psi-1}{\psi}} + (1-\beta)(g_S L_S)^{\frac{\psi-1}{\psi}}]^{\frac{\psi}{\psi-1}} \tag{3.5}$$

The share parameters α and $\beta \in (0,1)$, the factor augmenting terms g_U, g_K, and $g_S > 0$, and the substitution parameters σ and $\psi > 0$ are all technology parameters, and K, L_S, and L_U represent capital, skilled labor, and unskilled labor inputs, respectively. Given this production function, the elasticities of substitution between capital and unskilled labor and between skilled labor and unskilled labor are $\sigma_{KU} = \sigma_{SU} = \sigma$, while the elasticity of substitution between capital and skilled labor is $\sigma_{KS} = \sigma + \frac{1}{\theta_{KS}}(\psi - \sigma)$, where $\theta_{KS} \in (0,1)$ is the cost share spent on capital and skilled labor combined.[7] The production function exhibits capital-skill complementarity as defined in (3.4) when $\sigma_{KU} > \sigma_{KS}$, which in this case is equivalent to $\sigma > \psi$.

Consider this production function in a partial equilibrium framework in which the price of the final good is normalized to one, and real factor prices are exogenous. In this framework, the first order conditions can be subjected to shocks to the different technology parameters, allowing one to observe the resulting comovement between the error term in the decomposition equation and capital intensity, the regressor of interest.[8] For notational convenience, I set $\psi = 1$ in the following expressions, corresponding to the case in which the inner CES aggregate reduces to Cobb-Douglas, and capital-skill complementarity is equivalent to $\sigma > 1$. The results are similar to those in the general case, but can be demonstrated using much simpler expressions.[9]

[6] This functional form is used here for illustrative purposes, but similar forms have been used directly in empirical estimation in Krusell et al. (2000) and Duffy et al. (2004).

[7] Although Sato (1967) does not include the factor-augmenting technology parameters, these elasticities can be derived following similar calculations to those in the appendix of Sato (1967).

[8] An alternative approach would be to derive the cost function implied by (3.5) and take a second order log approximation, which would correspond to (3.1). Unfortunately with capital fixed, no closed form solution for this cost function exists, and calculating the necessary derivatives to implement the second order approximation using the implicit function theorem quickly yields intractable mathematical expressions.

[9] The Appendix presents the analysis in the general case in which the only restriction placed on the elasticity

The dependent variable in the decomposition regression is the wagebill share of skilled labor. The two-level CES production function, (3.5), yields a particularly unruly form for this share. However, since the wagebill share of skilled labor is increasing in L_S/L_U for a fixed wage ratio, one can infer the direction of change of the wagebill share of skilled labor by observing changes in L_S/L_U.[10] Taking the ratio of the first order conditions with respect to L_S and L_U and taking logs yields

$$\begin{aligned}\ln(L_S/L_U) =& \sigma \ln(\alpha/(1-\alpha)) + (1+(1-\beta)(\sigma-1))\ln(1-\beta) + \beta(\sigma-1)\ln\beta \\ & - (\sigma-1)\ln g_U + \beta(\sigma-1)\ln g_K + (1-\beta)(\sigma-1)\ln g_S + \sigma \ln w_U \\ & - (1+(1-\beta)(\sigma-1))\ln w_S - \beta(\sigma-1)\ln r \end{aligned} \tag{3.6}$$

where w_U, w_S, and r are the respective prices of unskilled labor, skilled labor, and capital. From this expression, it is clear that L_S/L_U is increasing in g_K, g_S, and α, and decreasing in g_U. Thus, in this model SBTC is associated with exogenous increases in g_K, g_S, and α, or decreases in g_U.[11]

The first order condition with respect to capital will demonstrate how capital intensity changes when the production function is subjected to SBTC parameter

parameters is the complementarity assumption that $\psi < \sigma$. The only substantive difference from the simpler $\psi = 1$ case concerns the parameters g_K and g_S. If $\psi \geq 1$ then the Cobb-Douglas case results continue to hold. Otherwise the signs of g_K's effect on K/Y and g_S's effect on L_S/L_U are ambiguous.

[10]The wagebill share of skilled labor is defined as

$$\frac{w_S L_S}{w_S L_S + w_U L_U} = \frac{\frac{w_S}{w_U}\frac{L_S}{L_U}}{\frac{w_S}{w_U}\frac{L_S}{L_U} + 1}$$

which is increasing in $\frac{L_S}{L_U}$ for a fixed wage ratio.

[11]The effects of changes in β on $\ln(K/Y)$ and $\ln(L_S/L_U)$ depend on the value of other parameters and input prices, and thus cannot be signed in general. However, taking the partial derivatives of (3.6) and (3.7) with respect to β, one can show that $\frac{\partial \ln(K/Y)}{\partial \beta} > 0$ whenever $\frac{\partial \ln(L_S/L_U)}{\partial \beta} > 0$. If this is the case, increases in β will induce positive bias in estimating ρ, as is the case with the other parameters. However, the bias could be negative or zero in other cases.

shocks. Taking logs of the first order condition with respect to capital yields

$$\begin{aligned}\ln(K/Y) =& \sigma \ln \alpha + (1-\beta)(\sigma-1)\ln(1-\beta) + (1+\beta(\sigma-1))\ln\beta + \beta(\sigma-1)\ln g_K \\ &+ (1-\beta)(\sigma-1)\ln g_S - (1-\beta)(\sigma-1)\ln w_S - (1+\beta(\sigma-1))\ln r\end{aligned} \tag{3.7}$$

This expression shows that K/Y is increasing in g_K, g_S, and α, and invariant to g_U. The likely endogeneity in the decomposition equation is apparent given these comparative static results. The SBTC-inducing parameter changes directly cause increases in capital intensity, with the exception of g_U which has no effect on capital intensity. Thus, the capital intensity term in (3.3) is likely to be positively correlated with SBTC shocks in the error term, and the OLS estimate of ρ will be biased upward, overestimating the effect of complementarity on the relative demand for skilled labor.

To see this bias more clearly, it is possible to use (3.6) and (3.7) to calculate the OLS estimate of ρ in (3.3) that would be obtained if the data used in estimation reflect the production technology just described. Following the previous literature, assume that the relative wage term in (3.3) is constant across industries and is therefore absorbed into the intercept term (see section 3.4 below). In this case,

$$\operatorname{plim} \hat{\rho} = \frac{\operatorname{Cov}\left(dS_{S,i}, d\ln \frac{K_i}{Y_i}\right)}{\operatorname{Var}\left(d\ln \frac{K_i}{Y_i}\right)}. \tag{3.8}$$

For small changes in $\frac{L_S}{L_U}$, the definition of $S_{S,i}$ implies that $dS_{S,i} = (S_{S,i} - S_{S,i}^2)\, d\ln \frac{L_{S,i}}{L_{U,i}}$. Assuming for simplicity that all industries begin with the same skill share, (3.8) can be restated as

$$\operatorname{plim} \hat{\rho} = \frac{(S_S - S_S^2)\operatorname{Cov}\left(d\ln \frac{L_{S,i}}{L_{U,i}}, d\ln \frac{K_i}{Y_i}\right)}{\operatorname{Var}\left(d\ln \frac{K_i}{Y_i}\right)}. \tag{3.9}$$

Given information on the variation in factor prices and technology parameters across industries, the covariance and variance terms in (3.9) can be calculated directly from (3.6) and (3.7), yielding the corresponding estimate of ρ.

In practice, the researcher estimating (3.3) observes variation in $d\ln(K_i/Y_i)$ that may be driven by capital price variation or by SBTC. Figure 3.2 uses (3.9) to show that the estimate of ρ increases as the variation in $d\ln(K_i/Y_i)$ is more heavily driven by SBTC, even when the degree of complementarity is held fixed. As an example of how the estimates in Figure 3.2 were calculated, consider the case where capital variation is driven only by cross-industry variation in the capital price r and the technology parameter α, and these two drivers are independent. The variation in $d\ln(K_i/Y_i)$ is then given by

$$\mathrm{Var}\left(d\ln\frac{K_i}{Y_i}\right) = \sigma^2\,\mathrm{Var}\left(d\ln\alpha_i\right) + \left(1+\beta(\sigma-1)\right)^2\mathrm{Var}\left(d\ln r_i\right), \tag{3.10}$$

with the first term on the right hand side describing the portion of the variation in $d\ln(K_i/Y_i)$ due to α-based SBTC and the second term describing the remainder of the variation due to r. The x-axis in Figure 3.2 represents the fraction of the total variation in $d\ln(K_i/Y_i)$ due to variation in the relevant SBTC parameter, so when this value is 0, all of the capital variation comes from r, and there is no variation in SBTC. The line labeled α in the left panel of Figure 3.2 shows how the estimate of ρ increases as the fraction of the variation in $d\ln(K_i/Y_i)$ due to α-based SBTC increases from 0 to 1 in the presence of complementarity (since $\sigma > \psi$). The line's intersection with the y-axis shows the correctly identified estimate of ρ, which is positive, indicating the presence of complementarity. As the variation in SBTC is increased, however, the ρ estimates increase, in spite of the fact that the substitution parameters are unchanged. A similar pattern is seen in the right panel of 3.2, in which production does not exhibit capital-skill complementarity (since $\sigma = \psi$). The ρ estimates only reflect the absence of complementarity when all of the capital variation is driven by variation in r, and the estimates of ρ are increasingly upward biased as SBTC variation becomes more important.

Figure 3.2 presents similar results for SBTC based upon variation in g_S and g_K, yielding the same conclusion. The degree of complementarity is correctly identified only when capital variation is driven by r and is overestimated when SBTC is present. Note that the estimates for g_S and g_K variation are identical in the left panel due to the Cobb-Douglas assumption ($\psi = 1$), and are absent from the right panel because neither parameter affects $d\ln(K_i/Y_i)$ in the absence of complementarity, so the x-axis is undefined. Estimate plots generated without the Cobb-Douglas restriction on ψ are presented in Figure 3.3, yielding the same qualitative conclusions.

This section has demonstrated that cost minimization implies that SBTC drives changes in both skill share and capital intensity. Therefore OLS estimates of the decomposition equation overestimate the effect of complementarity on skill demand.[12] The estimate plots in Figures 3.2 and 3.3 support this conclusion, and suggest that consistent identification can be achieved by using variation in capital intensity that is driven by cross-industry variation in the price of capital. The following section operationalizes this observation using an instrumental variables estimation strategy based on the tax treatment of capital.

3.4 Disentangling the Effects of Complementarity and SBTC

The preceding theoretical discussion suggests that the decomposition equation overestimates the effect of capital-skill complementarity on relative skill demand, and thus underestimates the residual effect attributed to SBTC. In an effort to assess this theoretical prediction, the remainder of this paper presents an instrumental variables analysis that takes advantage of changes in the U.S. corporate income tax

[12] BBG and others have included proxies of SBTC such as computer investment or R&D expenditures in an effort to directly measure the effects of technical change. While previous studies appear to have included these proxy variables for reasons other than concerns with endogeneity, a perfect measure of SBTC would completely remove it from the error term and resolve the endogeneity problem just discussed. However, the data previously used appear to be quite weak proxies for SBTC, and any cross-industry variation in SBTC that is not accounted for by the proxy will remain in the error term, continuing to cause biased parameter estimates.

code during the early 1980's. These changes resulted in cross-industry variation in the tax treatment of industry capital, which provide an instrument for the change in industry capital intensity. The results suggest that the theoretically predicted bias is realized empirically.

3.4.1 Corporate Income Tax and Effective Marginal Tax Rates

The corporate income tax in the U.S. is similar to a tax on corporate profits, allowing businesses to deduct input and materials costs that are incurred in generating revenues. Since capital inputs provide services over a long period of time and are "used up" slowly through economic depreciation, a textbook profits tax would allow businesses to deduct the value of economic depreciation incurred each year rather than the full price of the capital asset at the time of purchase. In practice, the U.S. corporate income tax has deviated from the textbook profits tax by providing investment tax credits allowing firms to immediately reduce tax liability by a fraction of a capital good's purchase price and by creating statutory depreciation schedules that differ substantially from economic depreciation rates. These deviations result in effective marginal tax rates that differ from the statutory tax rate.[13] Since the size of the investment tax credit and the gap between economic and statutory depreciation rates vary across capital assets, income from investment in different capital assets faces different effective marginal tax rates even though the statutory tax rate is the same across income from all assets. The empirical analysis presented here utilizes estimates of effective marginal tax rates on 28 different capital assets generated by Gravelle (2001) using the Hall and Jorgenson (1967) user cost of capital formula, which accounts for investment tax credits, statutory depreciation, economic depreciation, inflation, and interest rates.

[13]The effective marginal tax rate is defined as the marginal tax rate on true economic profits that would yield the same incentive to invest as the tax structure actually faced by the firm.

During the time period being examined, legislative changes greatly affected the tax treatment of capital investment.[14] The overall effect of these legislative changes was to generate significant variation in effective marginal tax rates across assets. In order to utilize this variation as an instrument for capital intensity in the decomposition regression, it is important that the investment incentives were not targeted toward capital assets that may embody SBTC. If such targeting did take place, the changes in tax rates might be correlated with SBTC shocks in the decomposition's error term and would not yield a valid instrument for changes in capital intensity. In its Report on the Economic Recovery Tax Act of 1981, the U.S. Senate Committee on Finance (1981) states that "tax reductions are urgently needed to stimulate capital formation," and goes on to note that the Act provides broad accelerated depreciation allowances for both plant and equipment capital assets. Neither the report nor the individual senators' additional comments mention targeting particular types of assets. These apparently ad-hoc investment incentives appear to have changed marginal tax rates in ways that do not exhibit any systematic pattern across asset classes. Table 3.1 reports the difference in the time averaged effective marginal tax rates in the 1975-79 and 1980-87 periods, and ranks the 28 asset classes by how much each was affected by the early 1980's tax changes. Assets of different types are quite evenly distributed throughout this ranking. For example, the six different classes of structures fall at ranks 7, 10, 15, 24, 25, and 26. High-tech equipment assets that are generally associated with SBTC, Office/Computing, Instruments, and Communications Equipment, fall at ranks 1, 19, and 27, respectively. Thus, it appears that the

[14]The Economic Recovery Tax Act of 1981 redefined depreciation categories, substantially increasing depreciation rates for most assets, and decreased the statutory tax rate on income from capital from 46% to 47%. Legislation during the 1981-85 period reduced the very large investment incentives of the 1981 Act. Finally, the Tax Reform Act of 1986 decreased the tax rate to 34% and sought to bring the system back in line with true economic depreciation by repealing many investment incentives and creating more variation in statutory depreciation rates across asset classes. See Auerbach, Aaron and Hall (1983); Gravelle (1994); and Gravelle (2001) for detailed summaries of the relevant changes in tax law.

tax changes did not target particular types of capital assets, and rather attempted to promote investment in general while affecting individual assets in essentially random ways. This suggests that industry tax changes provide a valid instrument for changes in capital intensity.

3.4.2 Data and Estimation

Equation (3.3) is estimated using data from the Annual Survey of Manufactures (ASM) in the NBER Manufacturing Productivity Database (Bartlesman and Gray 1996). As is common in studies of wage inequality, nonproduction and production workers respectively define skilled and unskilled workers. For comparison with previous results in the literature, this analysis follows a number of choices made by Berman, Bound and Griliches (1993) in implementing the estimation of (3.3). The relative wage term in the share equation is dropped due to a lack of data in the ASM on nonproduction worker hours. Under the assumption that any measured variation in relative wages across industries reflects unobserved quality variation within worker categories rather than true variation in relative wages for equivalent workers, it is appropriate to drop this term as it would be absorbed by the constant term if properly measured. Y is measured as shipments rather than value-added due to the lack of appropriate price deflators for industry value-added. As already mentioned, the technology term in (3.3), representing SBTC, is left in the error term. In an effort to reduce noise induced by measurement error in smaller industries in the ASM, data are weighted using the industry's share of the total manufacturing wage bill.[15] Finally, the results presented examine changes between 1979 and 1987. As seen in Card and DiNardo (2002), this was the period over which wage inequality exhibited the largest increase.

[15] See Berman et al. (1993) p.23 for a detailed discussion.

I use the change in the industry effective marginal tax rate on capital income as an instrument for the change in industry capital intensity. This approach directly corresponds to the definition of complementarity based upon elasticities of substitution - it examines changes in relative skill demand resulting from exogenous changes in the price of capital assets. The industry effective marginal tax rate is calculated as follows. Given the effective marginal tax rates for assets a in years t from Gravelle (2001), and assuming that a marginal investment will have the same asset mix as the industry's investments at a given point in time, t_0, an overall marginal tax rate on capital income in industry i can be constructed using a weighted average.[16]

$$\tau_i^t = \sum_a \kappa_{a,i}^{t_0} m_a^t \tag{3.11}$$

where τ_i^t is the industry-level measure of the effective marginal tax rate on capital income in industry i at year t, $\kappa_{a,i}^{t_0}$ is the weight for asset a in industry i at a given point in time t_0, and m_a^t is the effective marginal tax rate on asset a at year t. The asset weights, $\kappa_{a,i}^{t_0}$, reflect how much each industry utilizes each asset class, calculated here as the fraction of total industry i investment allocated to asset a as reported in the 1977 Benchmark Input-Output Accounts Capital Flow Tables (Silverstein 1985). This data set is published using the I-O Accounts industrial classification system, which includes 52 manufacturing industries corresponding to the 2- or 3-digit SIC level, each of which is assigned a tax rate for each year using equation (3.11). The change in the time averaged tax rate between the periods 1975-1979 and 1980-1987 is then used as an instrument for the change in capital intensity from 1979 to 1987.[17]

[16] Similar approaches are employed in Auerbach et al. (1983), Fullteron and Karayannis (1993), Gravelle (1982), Gravelle (1983), Gravelle (1994), and King and Fullerton, eds (1984)

[17] One potential concern with this technique stems from the way in which the Capital Flow Table was generated. As described in Bonds and Aylor (1998), certain types of aggregate equipment investment were allocated across industries based on an assumed mapping between occupations and equipment types. Given this assumption, an industry's occupational mix influenced the measure of its capital asset use. Thus, it is possible that the industry-level tax measure presented in (3.11) is correlated with the industry's skill intensity in 1977. If SBTC shocks arriving before 1977 were correlated with subsequent shocks, it is possible that the tax change instrument would be correlated

Since capital asset use data is available only by the I-O Accounts classification, the instrument varies only at the I-O Accounts industry level. Thus, all empirical results are reported with standard errors adjusted for 52 clusters at the I-O Accounts classification level, using the mapping from 4-digit SIC industries in the ASM to the I-O Accounts in Young (1991).

Table 3.2 presents OLS and IV estimates of the decomposition equation, (3.3), and Table 3.3 presents regression variable means. The OLS point estimates in Column (1) of Table 3.2 are identical to those in BBG Table 11, Column (1), although the standard errors presented here are somewhat larger due to clustering at the I-O industry level. As seen in previous work, the coefficient on $d\ln(K/Y)$ is positive, suggesting the presence of complementarity. Column (2) presents the IV results for the same specification, using the change in the industry effective marginal tax rate on capital income as an instrument for the change in capital intensity. As expected, the first-stage results indicate that industries facing larger tax cuts exhibited larger increases in capital intensity. The first-stage F statistic is 8.74. Based on the results in Stock and Yogo (2002), this F statistic is just large enough to allay concerns regarding large size distortions due to weak instruments.[18] The IV complementarity estimate is essentially zero, implying that the OLS results are biased upward, as expected based upon the theoretical discussion above. In keeping with the intuitive notion that equipment assets are more relevant to complementarity than structures, columns (3) and (4) report OLS and IV regressions examining equipment assets rather than combining equipment and structures. In this case, the instrument is

with SBTC shocks in the error term of (3.3), making the instrument invalid. This hypothesis relies on a correlation between the tax change instrument and the 1977 skill intensity. Since skill intensity is observable, it is possible to gauge whether the potential problem exists. The correlation coefficient between the tax change instrument and the 1977 skill intensity is extremely small, 0.0048, indicating that the cross-industry variation in the tax change was not influenced by the use of occupational mapping in the capital flow table.

[18]The F statistic of 8.74 is large enough to reject the null hypothesis that the actual size of a 5% test is greater than 20%, given the critical value Stock and Yogo (2002) of 6.66. It is nearly large enough to rule out smaller distortions as well - the critical value for the actual size of a 5% test is greater than 15% is 8.96.

calculated using only tax rates on equipment assets. The results are very similar to those in the first two columns, although the instrument is somewhat weaker in this case due to the decreased instrument variation resulting from the restricted set of assets.

Previous work often includes changes in structures intensity along with changes in equipment intensity and a separate regression term for changes in output to account for deviations from constant returns to scale. These terms are omitted from the present analysis due to a lack of available instruments. It is conceptually feasible to instrument for changes in structures intensity, just as for equipment intensity in column (4) of Table 3.2. Unfortunately, this is not practically possible in this case, due to the nature of the policy variation driving cross-industry variation in the instrument. Nearly all structures investment in manufacturing industries involves assets in the Industrial Structures and Commercial Structures classifications. As seen in Table 3.1, these two assets experienced nearly identical tax changes during the period being examined, so there is essentially no cross-industry variation in the tax treatment of structures that could be used to instrument for changes in structures intensity. However, with data on more detailed structures assets or a different tax policy change, the current methodology could in principle be used to generate a structures instrument. Output changes are omitted because they, like capital, are likely to be endogenous, but no instruments are readily available beyond the tax changes already being used to instrument for changes in capital intensity.[19] Thus, the approach developed here utilizes the constant returns assumption, which obviates the need for a separate term measuring changes in output.

[19] Dunne et al. (1997) and Duffy et al. (2004) instrument for changes in capital intensity and changes in output with flexible functional forms of lagged levels and changes in the regression variables. Given concerns about serially correlated SBTC shocks within industry potentially invalidating the exogeneity of lagged values as instruments, I have chosen to focus on policy-based instruments in this analysis.

The IV results in Table 3.2 imply that the OLS complementarity estimate is biased upward, as predicted in the theoretical analysis above. Columns (2) and (4) present the P-value from a Hausman test of the difference between the corresponding OLS and IV estimates, indicating that failing to instrument will lead to a statistically significant difference in the estimate for equipment. The negative point estimates in the IV regressions are somewhat surprising given that many previous studies have found capital-skill complementarity; Hamermesh (1993) concludes a review of the relevant empirical literature by stating "We are fairly sure that capital and skill are p-complements." However, the same review discusses a number of individual studies finding no complementarity or even complementarity between capital and unskilled labor, and the results of a number of the studies finding complementarity in translog production systems are "not robust to whether assumptions of symmetry and homogeneity are imposed on the translog system." Noting this variation in previous findings, the present estimates are less surprising.

The results presented here provide evidence against the strong complementarity found in previous studies estimating the share equation and support the theoretical finding that OLS estimates are biased upward. However, the IV estimates are somewhat imprecisely estimated, and they do not rule out small positive complementarity estimates. Thus, although the present results do indicate upward bias in previous estimates, they should not be taken as strong evidence against smaller levels of complementarity. The IV approach developed here could be used to generate more precise estimates given more detailed data on how industries use different capital assets. Since the capital asset data used here varies only across 52 industries, clustering at this level implies that the analysis essentially uses only 52 observations. The U.S. Census Bureau's Annual Capital Expenditure Survey included questions regarding

investment by detailed asset class in its 1998 and 2003 surveys, with the expectation of continuing to ask these questions every five years (U.S. Census Bureau 2005). Although this data source began after the period of sharply increasing inequality of interest in the present study, it could provide future investigations with asset use data for more detailed industries, hopefully allowing for greater instrument strength and more precise estimates.

3.5 Conclusion

This analysis has demonstrated that cost function estimates in many recent studies of wage inequality systematically overstate the influence of capital-skill complementarity on increases in relative skill demand. This bias results from the assumption of quasi-fixed capital in the presence of skill-biased technological change. Although this finding is consistent with the inequality literature's consensus that complementarity alone cannot account for the observed increases in skill demand during the 1980's, an accurate measure of complementarity is of independent interest in many areas of labor demand and when evaluating policies that affect the price of capital. The instrumental variables analysis confirms the theoretical prediction that standard OLS estimates overestimate complementarity. In fact, the IV estimates are indistinguishable from zero and rule out large complementarity estimates. Since much of the recent evidence in favor of complementarity comes from studies utilizing the cost function approach, these contrary results suggest a need to further investigate the extent of capital-skill complementarity in manufacturing production using alternative methods. The tax-based instrumental variables approach presented here represents one possible approach that could be used to examine complementarity following future tax changes.

3.6 Appendix: Two-Level CES Production Function with General Parameter Values

The analysis presented above imposes $\psi = 1$ in (3.5) for simplicity. Without imposing the restriction that $\psi = 1$, the primary complication is that the unit price of Z, the capital-unskilled labor aggregate, has the following form:

$$\lambda = \left[\beta^{\psi} \left(\frac{r}{g_K} \right)^{1-\psi} + (1-\beta)^{\psi} \left(\frac{w_S}{g_S} \right)^{1-\psi} \right]^{\frac{1}{1-\psi}}$$

As this term does not log-linearize to a convenient expression, it generates very complex comparative static results for factor demands. For completeness, the general case factor demands are as follows.

$$\frac{L_U}{Y} = \left(\frac{1-\alpha}{w_U} \right)^{\sigma} {g_U}^{\sigma-1}$$

$$\frac{K}{Y} = \alpha^{\sigma} \beta^{\psi} {g_K}^{\psi-1} r^{-\psi} \lambda^{\psi-\sigma}$$

$$\frac{L_S}{Y} = \alpha^{\sigma} (1-\beta)^{\psi} g_S^{\psi-1} w_S^{-\psi} \lambda^{\psi-\sigma}$$

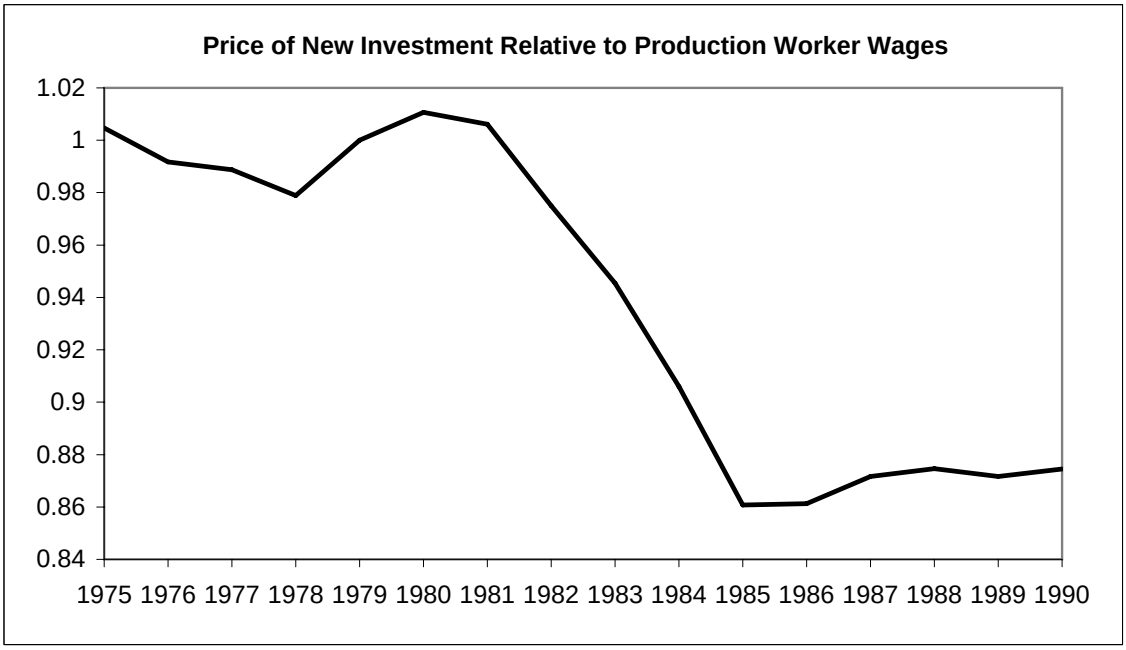
As described in the text, taking logs of these factor demands allows determination of the effect of each parameter on the elements of the decomposition regression, K/Y and L_S/L_U. Given the complementarity assumption that $\psi < \sigma$, the results of this exercise are as follows.

Positive changes in α cause positive changes in both L_S/L_U and K/Y. The effects of β remain ambiguous. Increases in g_U have no effect on K/Y and cause positive (negative) changes in L_S/L_U if $\sigma < 1$ ($\sigma > 1$). Increases in g_K cause positive changes in L_S/L_U and cause positive changes in K/Y if $\psi \geq 1$ (otherwise the effect on K/Y is ambiguous). Increases in g_S cause positive changes in K/Y and cause positive changes in L_S/L_U if $\psi \geq 1$ (otherwise the effect on L_S/L_U is ambiguous). Thus the conclusions in the text hold, with the added restriction that $\psi \geq 1$ to determine the

effects of g_K and g_S. Note, however, that Krusell et al. (2000) estimate $\psi = 0.67$ and $\sigma = 1.67$, which is consistent with the complementarity assumption, but not with the restriction that $\psi \geq 1$.

3.7 Figures and Tables

Figure 3.1: Movement in the Price of New Investment Relative to Production Worker Wages



Source: Author's calculations based on Annual Survey of Manufactures data and price indices provided in the NBER Manufacturing Database (Bartlesman and Gray, 1996)

Notes: Production workers' wages calculated as production worker wagebill divided by production worker hours

Each yearly observation is a weighted sum of industry-level values for that year with weights equal to the industry's share of total yearly manufacturing wage bill

Values normalized to equal 1.0 in 1979

Figure 3.2: Complementarity estimates implied by 2-Level CES production function

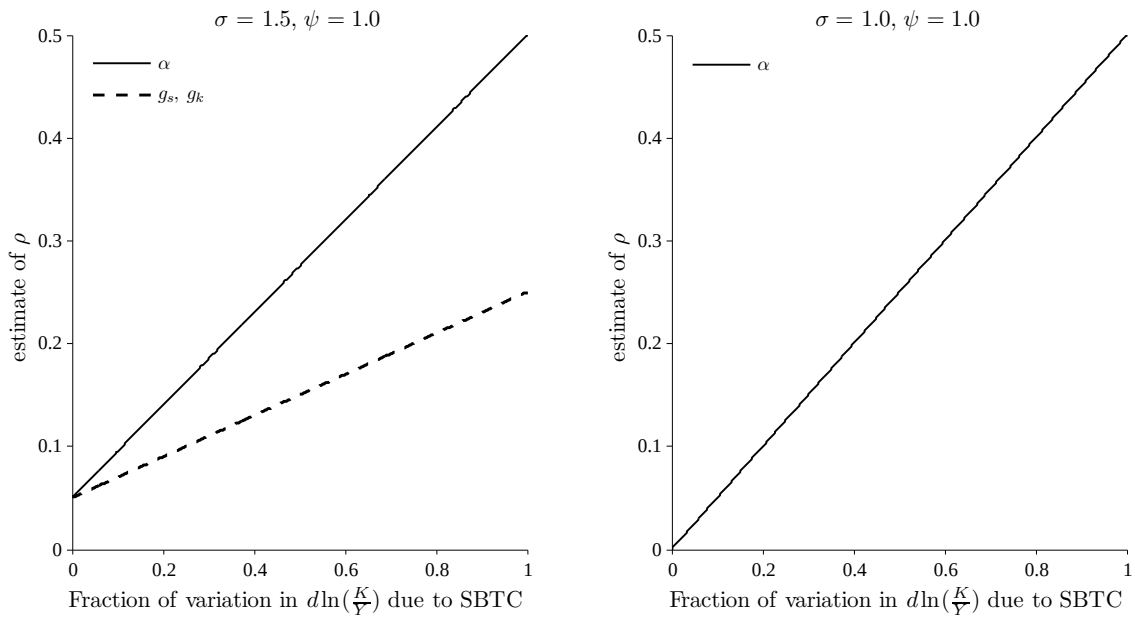


Figure 3.3: Complementarity estimates implied by 2-Level CES production function - without Cobb-Douglas restriction on ψ

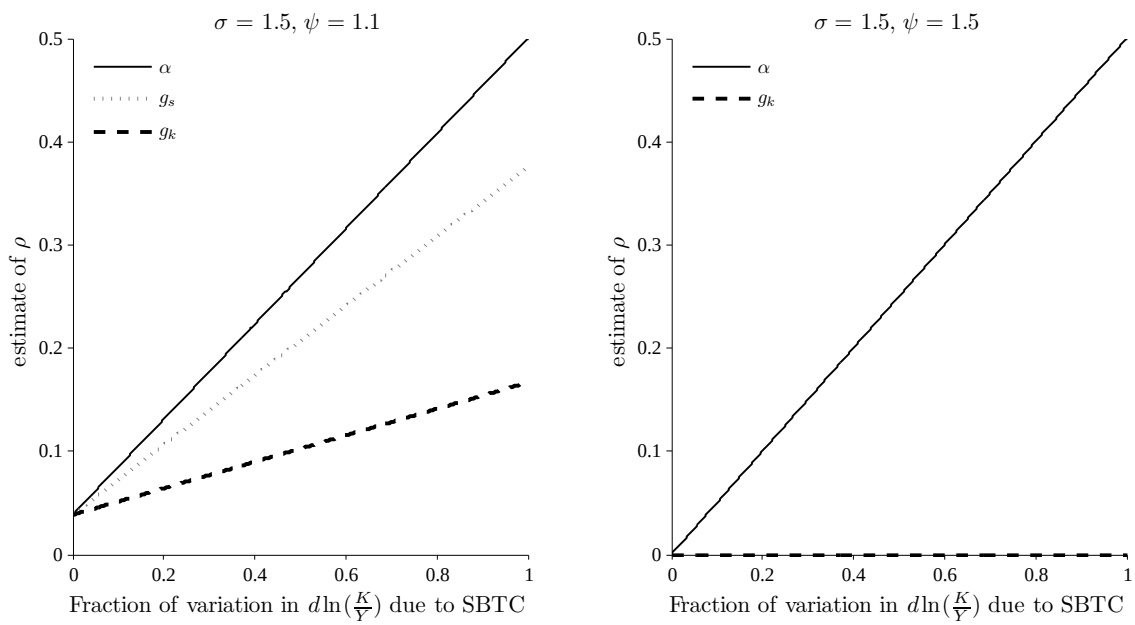


Table 3.1: Changes in Average Effective Marginal Tax Rates

Rank	Asset	Average MTR 1975-79	Average MTR 80-87	Difference
1	Office/Computing	-8.0	9.0	17.0
2	Trucks/Buses/Trailers	7.0	10.1	3.1
3	Construction Machinery	5.0	8.0	3.0
4	Agricultural Equipment	4.0	6.8	2.8
5	Tractors	6.0	8.6	2.6
6	Furniture and Fixtures	5.0	7.3	2.3
7	Mining Structures	12.0	11.5	-0.5
8	Other Equipment	13.0	9.4	-3.6
9	Railroad Equipment	28.0	24.4	-3.6
10	Public Utility Structures	30.0	26.1	-3.9
11	Other Electrical Equipment	12.0	8.1	-3.9
12	Special Industrial Equipment	12.0	7.9	-4.1
13	Engines and Turbines	36.0	31.5	-4.5
14	Metalworking Machinery	13.0	8.4	-4.6
15	Farm Structures	44.0	37.8	-6.3
16	Mining/Oilfield Equipment	17.0	10.3	-6.8
17	Autos	19.0	12.0	-7.0
18	Aircraft	18.0	11.0	-7.0
19	Instruments	22.0	14.9	-7.1
20	Electric Transmission Equipment	33.0	25.6	-7.4
21	General Industrial Equipment	23.0	14.0	-9.0
22	Fabricated Metal	30.0	20.4	-9.6
23	Service Industry Equipment	22.0	10.9	-11.1
24	Commercial Structures	51.0	39.4	-11.6
25	Other Structures	57.0	45.4	-11.6
26	Industrial Structures	54.0	42.0	-12.0
27	Communications Equipment	25.0	9.0	-16.0
28	Ships and Boats	32.0	10.0	-22.0

Source: Calculations derived from data presented in Gravelle (2001)

Table 3.2: Share Equation Estimates - All Industries

dependent variable: change in non-production workers' wage bill share (d Ss)

Equation	(1) OLS	(2) IV	(3) OLS	(4) IV
d ln(K/Y)	0.028	-0.012		
	(0.018)	(0.031)		
d ln(E/Y)			0.030	-0.041
			(0.017)+	(0.034)
Constant	0.437	0.482	0.414	0.542
	(0.073)**	(0.067)**	(0.070)**	(0.067)**
R^2	0.028		0.036	
1st stage coefficient		-1.499		-0.959
on tax instrument		(0.507)**		(0.424)*
1st stage F		8.74		5.11
Hausman test P-value		0.131		0.046*

Sample: Annual Survey of Manufacturers, 450 manufacturing industries

Standard errors adjusted for 52 clusters at the I-O accounts industry classification level

The d operator represents long differences over the 1979-1987 range, divided by 8 for yearly changes

Data weighted by industry share of total manufacturing wage bill, averaged between 1979-1987

+ significant at 10%; * significant at 5%; ** significant at 1%

Table 3.3: Regression Variable Means - All Industries

Variable	Mean
d Ss	0.468
d ln K	2.807
d ln E	3.492
d ln Y	1.693
d ln(K/Y)	1.113
d ln(E/Y)	1.799

Sample: Annual Survey of Manufacturers, 450 manufacturing industries

All differences represent changes over the 1978 - 1987 range, divided by 8 for average yearly changes

Data weighted by industry share of total manufacturing wage bill, averaged between 1979 and 1987

CHAPTER IV

Offshoring and Price Measurement in the Semiconductor Industry

4.1 Introduction

The recent growth in offshore outsourcing of intermediate input production has generated concern that standard government data collection methods are ill-suited to an increasingly international productive structure (Houseman 2007). This paper focuses on the semiconductor industry to estimate the effects of offshore outsourcing on input price measurement. We find that offshoring in this industry necessitates the collection of very detailed product data to adequately adjust prices for input quality, and that shifting sourcing patterns may cause standard price measures to understate price declines for processed semiconductor wafer inputs by as much as 0.8% per year.[1]

We choose to examine wafer fabrication, an intermediate stage in semiconductor production, for a number of reasons. First, semiconductor wafer production has moved offshore to a dramatic degree in the last forty years, with continual shifts in the geographic distribution of semiconductor manufacturing capacity. Second, China's entrance in the semiconductor manufacturing market in 2001 was much heralded in the media, and provides an interesting case study on the effects of growing

[1] Semiconductor wafers are described in detail in Section 4.2.

Chinese economic strength on an important industry. Third, the discrete nature of technological progress in semiconductor wafer fabrication techniques makes careful quality adjustment feasible, as we describe in detail below. Finally, we have obtained a new dataset of semiconductor input prices with information on country of origin, making possible an empirical investigation of the effects of shifts in sourcing on input price measurement.

Offshoring poses a number of challenges for price measurement in the semiconductor manufacturing sector in particular. First, suppose a U.S.-based manufacturer contracts out all production to a firm overseas and that, prior to its decision to offshore, it had purchased final goods from an independent supplier here in the U.S. or had made the good itself. The one-time decline in the price level associated with the decision to offshore is not captured by current data-collection procedures. The Producer Price Index's universe does not include imports, so it does not reflect the price reduction. The Bureau of Labor Statistics (BLS) International Price Program (IPP) measures price changes beginning in the *second* month in which the imported good is observed, as it is not designed to measure the initial price decline that occurs when a domestic producer first off-shores a segment of production. A similar problem can arise if the firm has already contracted out production overseas but now sources from a low-cost supplier in China rather than from a producer in Taiwan.[2]

The problem posed by shifting sourcing arrangements is essentially equivalent to the problem of outlet substitution bias in the CPI, described in detail by the Boskin Commission Report (Boskin, Dulberger, Gordon, Griliches and Jorgenson 1996) and Diewert (1998). While those studies were concerned with consumers shifting their

[2]In principle, the IPP would measure this change if the manufacturer imported the good itself or if it continued to work through the same intermediary that is surveyed by IPP. If, on the other hand, the manufacturer contracts with a different intermediary in order to access a new market overseas, the IPP will miss the price decline since it surveys the importer, which in this case was the original intermediary. Unfortunately, to the best of our knowledge, there is little information on the relative importance of intermediaries in the IPP.

consumption toward low-cost retail outlets, this paper confronts the problem of semiconductor producers shifting their intermediate input sourcing toward low-cost suppliers located abroad. The bias is most acute whenever the inputs, as in our case, are approximately identical, which implies that the unmeasured price change when production is shifted to a new location does in fact represent a genuine price decline for the same good.

The final significant challenge is quality adjustment. As a greater share of production is shifted abroad, the composition of imports becomes increasingly sophisticated. This is particularly true within the semiconductor industry, which imports many complex intermediate inputs at various stages in the production process. This process places much greater demands on quality adjustment procedures for import prices, as semiconductor technology changes so quickly. The challenge of quality adjustment in the semiconductor industry is well known and has been demonstrated in many previous studies.[3]

We address these concerns using new transaction-level data on semiconductor wafer purchases, collected by the Global Semiconductor Alliance (GSA). These data contain fine detail on product characteristics, allowing us to generate constant-quality price indexes. They also report the source country for each transaction, making it possible to examine the effects of shifting geographic production on price measurement. Our results demonstrate the importance of having such detailed data when constructing price indexes in industries with large amounts of offshoring. This need is likely to increase as more countries move up the technical ladder and begin exporting ever more complex products.

The paper proceeds as follows. Section 4.2 describes aspects of the semiconductor

[3]See, among others, Flamm (1993), Grimm (1998), and Aizcorbe, Corrado and Doms (2003).

manufacturing process that are relevant to price measurement. Section 4.3 describes the data we utilize to build input price measures. Section 4.4 presents our price index calculations. We begin with a standard matched model index as a baseline and then follow Reinsdorf (1993) to bound the potential effect of outlet substitution bias due to shifting input sourcing across countries. This section concludes with comparisons to a hedonic index and a publicly available official semiconductor price index. Section 4.5 concludes.

4.2 Semiconductor Production

This section describes the semiconductor manufacturing process and recent changes in the business models employed by semiconductor firms, highlighting characteristics of the industry that are important for price measurement. Semiconductor production technology progresses in distinct measurable steps, allowing us to account for technological improvement when constructing price indexes in spite of rapid changes over time. The continuing movement to outsource semiconductor production to offshore firms raises the possibility of outlet-substitution bias in standard price indexes and motivates our choice to focus on foundry wafer fabrication.

4.2.1 Semiconductor Production Technology

Semiconductor fabrication involves creating networks of transistors on the surface of a thin piece of semiconducting material.[4] The process begins with the design and layout of a new chip. Semiconductor designers use suites of complex software to specify the functionality of the chip, convert that logic into the corresponding network of transistors, determine the physical layout of those transistors, and simulate the behavior of the proposed design for debugging purposes.

[4] Turley (2003) provides an accessible overview of semiconductor technology, manufacturing, and business.

Semiconductors are manufactured in a facility called a fab. Transistors are created on the surface of the wafer through a photolithography process, in which successive layers of conducting and insulating materials are deposited on the surface of the wafer and chemically etched away in the appropriate places to form the desired pattern of transistors and necessary interconnections. The design layout software determines the etching pattern for each layer, which is projected onto the wafer through a mask containing the negative of the desired pattern, in a process similar to developing a photograph by projecting light through a negative. Each step of the etching process is repeated multiple times across the wafer, resulting in a grid pattern of many copies of the chip. Once all transistors and connection layers are complete, the chips are tested in a process called "wafer probe," and any faulty chips are marked to be discarded. The wafer is then cut up, leaving individual chips, called die. The die are then placed inside protective packages and connected to metal leads that allow the chip to be connected to other components.

Semiconductor fabrication technology has advanced over time in discrete steps, defined by wafer size and line width (also called feature size). Increases in wafer size allow larger numbers of chips to be produced on a wafer. Most fabs currently produce 150mm (roughly 6 inches), 200mm (8 inches), or 300mm (12 inches) diameter wafers. Although larger wafers cost more to produce, the move to a larger wafer has generally reduced the cost per die by approximately 30% per die (Kumar 2007).

Line width is the size of the smallest feature that can be reliably created on the wafer. Decreased line width means that individual transistors are smaller, and more functionality can be integrated into a given area of silicon. This makes chips of a given functionality smaller, lighter, and faster, and also makes it feasible to include more functions on a single chip. The number of transistors that can be produced on a

chip has grown exponentially over time, following Moore's Law, the Intel co-founder's famous observation that the number of transistors on a chip doubled every eignteen months (Moore 1965).[5] Figure 4.1 shows the maximum number of transistors per chip and the minimum line width used to produce Intel processors over the last 40 years (both plotted on logarithmic scales).

Current line widths are measured in microns (μm) or nanometers (nm). The smallest line width currently being produced in volume is 25nm. As a rule of thumb, Kumar (2007) estimates that moving a given chip design to a 30% smaller line width will result in cost savings of approximately 40%, assuming the same number of defects in both processes. The primary drawback of smaller line widths is increased cost per wafer, particularly early in the technology's life span. Masks are much harder to produce when creating smaller features, and new process technologies often result in higher defect rates and lower yields, the fraction of chips on a wafer that function correctly. In spite of these challenges, the benefits of increased die per wafer and better performance outweigh the problems of decreased yields, particularly as the fabrication technology matures and yields increase. Given the benefits of smaller line widths, semiconductor manufacturers have steadily moved toward newer technology. This is apparent in Figure 4.1 for Intel processors and can be seen even more clearly in Figure 4.2, which plots the technology composition of sales at Taiwan Semiconductor Manufacturing Company (TSMC), the largest semiconductor foundry.

There are a number of options regarding the chemicals used to create the transistors themselves and how the transistors are arranged to implement logical functions. The most common technology, called complementary metal-oxide semiconductor (CMOS), accounted for 97% of worldwide semiconductor production in 2008.[6]

[5] This regularity later slowed to doubling every two years.

[6] Share of actual wafer starts reported in SICAS Semiconductor International Capacity Statistics.

Other transistor arrangements, such as bipolar logic, and other chemical processes, such as Gallium Arsenide (GaAs) or Silicon Germanium (SiGe), generally focus on niche markets for high-frequency, high power, or aerospace devices, rather than the storage and computational logic products comprising the majority of the CMOS market. In the following analysis, we will refer to each combination of wafer size, line width, and logic family as a "process technology" (e.g. 200mm, 180nm, CMOS constitutes one process technology).

The price index calculations below require us to define the set of product characteristics that determine the performance, and hence the price, of a given wafer. To guide this choice, we have consulted pricing models used by engineers at fabless firms to estimate production costs when developing business plans. Kumar (2008) presents a wafer cost model based on wafer size, line width, and logic family. A commercial cost estimation firm, IC Knowledge, distinguishes wafer cost estimates by wafer size, line width, logic family, number of polysilicon layers, and number of metal layers. Given this potential importance of the number of layers in a given design, indicating the design's complexity, we calculate price per layer rather than price per wafer. These pricing models support the use of process technology (wafer size, line width, and logic family) to distinguish between goods in our price indexes, calculated in Section 4.4.

4.2.2 Changing Semiconductor Business Models

In the early 1970's nearly all semiconductor producers were vertically integrated, with design, wafer fabrication, packaging, testing, and marketing performed within one company. By the mid '70's, firms began moving packaging and test operations to East Asia to take advantage of lower input costs (Scott and Angel 1988, Brown and Linden 2005). In spite of outsourcing these relatively simple steps in the produc-

tion process, firms maintained their complex wafer fabrication operations in house. Firms that perform both design and wafer fabrication are referred to as Integrated Device Manufacturers (IDM). As wafer fabrication technology advanced, the cost of production facilities increased dramatically; the cost of a fabrication facility has risen from $6 million in 1970 (IC Knowledge 2000) to $4.2 billion in 2009 (Global Foundries 2009). This sharp increase in cost has made it ever more difficult to stay at the leading edge of process technology. In the mid 1980's, small semiconductor firms began producing some of their more advanced designs on the manufacturing lines of larger, more established semiconductor manufacturers that were better able to bear the capital costs of maintaining a state-of-the-art fab facility. Many Japanese semiconductor firms had substantial excess manufacturing capacity during this time period, making such production partnerships particularly attractive (Hurtarte, Wolsheimer and Tafoya 2007).

These production sharing arrangements led to the creation of a new business model through the emergence of wafer foundries that manufacture semiconductors designed by other firms. At first, foundries were used by IDMs as an alternative source of capacity for older process technologies (Kumar 2008). By the late 1980's a number of new semiconductor firms avoided wafer fabrication by doing all of their manufacturing through foundries. Semiconductor companies with little or no in-house wafer manufacturing capability are called "fabless" firms. In general, fabless firms perform chip design and layout, and use foundries and other contractors for mask production, wafer fabrication, packaging, and testing. The fabless business model has grown quickly over the last 30 years, accounting for 24% of total semiconductor industry revenue in 2009, as shown in Figure 4.3.[7] Since the largest foundries are located in

[7]Note that the shares in Figure 4.3 are likely to understate the extent of fabless production activity because companies must derive 75% or more of their semiconductor revenue from fabless production. Many companies not counted as fabless nevertheless rely heavily on foundries

Asia, and the largest fabless semiconductor producers are located in North America and Europe, the growth of the fabless model has increased the internationalization of semiconductor production.[8] Although the fabless share of the global semiconductor industry only edged up from 2006 to 2008, as new process technologies continue to raise the costs of fab facilities, the prominence of the fabless model may well increase even more. Indeed, AMD, the second largest microprocessor producer, spun off its manufacturing division as an independent foundry company in 2009, boosting the fabless share of the industry (Clendenin and Yoshida 2002).[9]

4.2.3 Implications for Price Measurement

The extremely fast pace of technological change in semiconductor manufacturing poses a large challenge to quality-adjusted price measurement. Aizcorbe (2002) demonstrates the difficulty government price indexes have had in tracking rapid price declines in finished semiconductors. However, as just described, technological advance in semiconductor production proceeds in discrete, measurable steps, in contrast to continuous and difficult to measure quality improvements seen in other industries (Flamm 1993). This discrete nature of technological advance in the semiconductor industry makes it possible to control for quality changes, given detailed enough data on product characteristics. In this study we construct constant-quality price indexes for wafer fabrication using quarterly pricing data that includes the most relevant aspects of process technology: wafer size, line width, and logic family. We also control for the number of layers used in constructing the chip, a proxy for design complexity.

[8] In 2008, the 5 largest foundries (accounting for 84% of foundry revenue) were all located in Asia. Of the 25 largest fabless semiconductor companies (accounting for 75% of fabless revenue), 19 were located in North America or Europe. These figures were calculated from proprietary reports from iSuppli and GSA, respectively.

[9] A recent report (IC Insights) predicts that between 2008 and 2013, total foundry sales will grow at double the rate of the overall semiconductor industry.

This section has also documented the increasing internationalization of the semiconductor supply chain coinciding with offshoring various steps in the production process and the growth of the fabless model of semiconductor production. Houseman (2007) describes the challenges faced by statistical agencies attempting to measure price changes when producers switch suppliers, particularly when the suppliers are located abroad. In particular, substitution toward low-cost suppliers is likely to be missed in standard price index calculations (see below for a more detailed discussion), understating the rate of input price decline. As semiconductor production technology advances and the fabless business model becomes more prominent, it is likely that these price measurement challenges will remain relevant in the foreseeable future.

In the remainder of this paper, we focus on foundry wafer production, leaving analysis of IDM production for future work. We make this choice for practical reasons. Our pricing data include only wafer purchases from foundries, though those purchases could have been made by fabless firms or IDM's choosing to use foundry suppliers. Also, the issue of within-firm transfer pricing raises a number of complications that are beyond the scope of this study and makes data collection essentially impossible.

4.3 Data Sources and Descriptive Results

To construct the price indexes used in our analysis, we require information on prices paid and quantities purchased for foundry services, specified by the characteristics relevant for pricing. We obtain prices from a survey conducted by the Global Semiconductor Alliance (GSA) and we calculate quantities by merging several dif-

ferent sources.[10] Observations are quarterly, and our data span the period from 2004 to 2008. Descriptive results demonstrate the importance of controlling for process technology. They also reveal substantial shifting of production toward lower cost countries.

4.3.1 Wafer Pricing Survey

Our primary dataset consists of 7,455 individual responses to GSA's *Wafer Fabrication & Back-End Pricing Survey*, provided to us for 2004 to 2008.[11] The survey has been conducted quarterly since 2004 and provides extensive detail on contracts for foundry services, including key technological features, foundry location, price paid, and volume for a diverse set of foundry customers. The survey responses account for a representative sample of about 20 percent of the wafers processed by the foundry sector.

As shown in Table 4.1, we drop observations missing key variables. We also drop observations reporting prices for engineering runs, preliminary fabrication before volume production. To focus on substitution between onshore and offshore production, and between offshore locations, we retain only contracts for production at the major offshore locations (Taiwan, Singapore, and China), U.S. foundry contracts, and European contracts for comparison.[12] A small number of observations with internally inconsistent responses are dropped, as are the handful of observations on 100mm wafers - a very dated technology. All told, we use 5,464 observations for index construction.

[10] GSA is a semiconductor trade association whose membership includes fabless producers and IDMs. It survey is administered to members and non-members.

[11] Individual respondents are not identified in our data.

[12] Significant omissions from the global foundry industry are Japan and Korea. Our approach to estimating capacity, described below, does not allow us to assign reasonable weights on technologies in Korea. Our preliminary price index for Japan behaved erratically, and suggested that the product composition was changing in a way not captured by our data. We have obtained more detailed data extracts that may assist in alleviating this problem in subsequent versions.

4.3.2 Descriptive Price Results

Descriptive statistics for key variables in the resulting dataset are shown in Table 4.2. We observe 273 prices per quarter, on average. Wafer prices average $1,575 over the period covered. Interestingly, no substantial time trend is evident before adjusting for composition. The average contract was for 2,307 wafers, and the average contract size climbs over time. The number of layers per wafer also rose significantly over the period studied, from 23 in 2004 to 28 in 2008, reflecting a trend toward foundries handling increasingly complex products.

The changing technological characteristics of the fabrication process are evident in the statistics for wafer diameter and geometry. Pilot lines for 300 mm wafers were first introduced in 2000 and the share for this emerging technology rises from 3.5 percent of contracts to 20 percent of contracts over the survey. Similarly, new generations of lithography increase in penetration over time: 90 nanometer technology reached volume production in the overall semiconductor industry in 2004 and slowly gained share in the foundry market, ending at 7 percent in 2008; 65 nanometer contracts were just emerging in 2008.[13] Meanwhile, older technologies, with processes above 250 nanometers, dwindle in prominence from 45 percent in 2004 to 28 percent in 2008. 92 percent of contracts reported in the survey are for CMOS technology, but prices are available for other processes as well.

A challenge with the GSA pricing survey is sporadic reporting for some technologies in certain geographic regions, despite independent evidence that such production existed. For such cells where we believe there was production (based on our capacity database described in the next subsection) we linearly interpolate prices using values

[13] 2004 and 2007 mark the years when volume production of DRAM began at 90nm and 65nm, respectively (*International Technology Roadmap for Semiconductors* 2007).

from surrounding periods or extrapolated based on higher-level prices.[14]

4.3.3 Quantities and the Shifting Geography of Production

To construct a price index, we need to weight individual price observations by quantity. Although the GSA survey includes information on the size of each order, some gaps in reporting remain. This makes weights based on the GSA data unstable at quarterly frequencies. As an alternative, we construct weights based on global foundry capacity. Although capacity is an imperfect proxy for actual production or purchases, we must choose between erratic sales measures and highly credible capacity estimates. Our baseline index uses the latter.

The Gartner *Semiconductor Fab Database* provided us with quarterly capacity data from 2004 to 2007. For specific fabs, key features are reported, including planned wafer start capacity, minimum line width, operating status, and whether the fab was operating as a foundry. We extended these data with GSA's *2009 IC Foundry Almanac* which provides a snapshot of capacity and technology by fab as of 2009.

Merging these data sets gives us a preliminary set of weights, but we address three remaining shortcomings. First, Gartner only reports planned capacity by fab and ramp-up status, leaving the contours of the ramp-up process unknown. Fortunately, many major foundries provide quarterly information on actual operational capacity, showing the actual path of capacity as equipment is added incrementally. We employ these directly reported capacities, when available, and add a comparable ramp-up period to fabs for companies without direct reporting.[15] Second, the data do not distinguish CMOS production quantitatively, though GSA does indicate whether a

[14]Note that the alternative, dropping these periods for lack of directly observed prices, is not neutral, since it amounts to 1) assuming the product mix within the industry is different than we know it is, and 2) throwing out price information from this period for cells with similar technology or geography. See discussion of this approach in Gordon (2006).

[15]Ramping new capacity to volume production typically takes 12 months (*International Technology Roadmap for Semiconductors 2007)*

fab uses CMOS and other processes. Since CMOS prices behave rather differently than non-CMOS prices, we assigned a weighted average of the CMOS and non-CMOS prices to each fab for the technology in operation, using overall industry weights from the GSA. Third, in the Gartner fab database, we only observe the minimum line width in use at a fab, but we know that fabs often operate multiple geometries one time. This raises the possibility that we *overweight* leading edge technologies. On the other hand, it is important to bear in mind that we only observe capacity, not actual production. Since capacity utilization is higher for leading edge geometries, the application of capacity weights generates a bias in the opposite direction – toward *underweighting* these geometries.[16]

Table 4.3 compares two aggregate measures of foundry capacity, constructed as just described, to industry estimates from other sources. First, wafer fab capacity as reported to the SICAS survey suggests our wafer fab measure is not fully capturing the overall size of the sector. However, the growth rate from 2004 to 2008 for the measure constructed from our bottom-up approach is very close to the SICAS measure, suggesting we are catching the overall trend in industry capacity. Our measure of revenue is also somewhat lower than the measure of foundry company revenue published by the consultancy iSuppli. This may simply reflect that not all foundry revenues are for the services we are studying. Table 4.4 shows shifting revenue weights among the largest offshore foundry suppliers. While Taiwan's share falls somewhat, China and Singapore both gain revenue share, representing movement toward lower cost foundry locations.

[16]Utilization on fab lines using 90nm and smaller geometries was 94% in 2007, noticeably higher than the 86% utilization for larger geometries (SICAS 2008).

4.4 Price Index Results

This section presents our price index calculations using the database just described. The level of detail in our data allows us to adjust for differences in physical product attributes. In addition, since our data also includes foundry location, we are able to isolate the effect of shifting production across countries on the average wafer price. We find that substitution across countries may account for no more than a 0.8 percentage point per year decline in the average wafer price. Our findings also support the established importance of careful quality adjustment to capture the effects of rapid technological change on semiconductor prices.

4.4.1 Fisher Matched Model Index

Our data set includes price information by detailed semiconductor wafer type and source country at the quarterly frequency. As discussed in Section 4.2, a wafer's process technology (defined by wafer size, line width, and logic family) determines its performance, along with circuit design. Process technologies proceed in discrete steps, so our detailed data on prices by process technology yields a time series of price observations for each wafer type, with attributes held constant over time. This high level of detail allows us to construct a matched model price index tracking quarterly price changes for each wafer type.

The matched model index is calculated as a Fisher index of price relatives for each process technology and country pair. First we calculate Laspeyres and Paasche indexes, respectively, as

$$P_L^t = \sum_i \sum_j s_{ij}^{t-1} \frac{p_{ij}^t}{p_{ij}^{t-1}} \tag{4.1}$$

$$P_P^t = \left[\sum_i \sum_j s_{ij}^t \left(\frac{p_{ij}^t}{p_{ij}^{t-1}} \right)^{-1} \right]^{-1} \tag{4.2}$$

where i represents process technology, j represents source country, t is time (quarter), and p is the average price for a given process technology, country, and quarter in the GSA survey.[17] s is the share of total output value in time t accounted for by wafers in the relevant process technology and country cell, calculated using our capacity database. As the Laspeyres index overstates price changes and the Paasche understates them, it is advisable to construct the Fischer index, which is a geometric mean of the Laspeyres and Paasche indexes.

$$P_F^t = \sqrt{P_L^t \; P_P^t} \tag{4.3}$$

We normalize the index to 100 in the first quarter of 2004.

The procedure just described treats observations from different source countries as separate "models" by calculating separate price relatives by country. This parallels the treatment of prices across outlets in the U.S. CPI, and is subject to similar assumptions (Reinsdorf 1993). When a new process technology and country combination appears, it is assumed that any difference in the price *level* across countries for that process technology entirely reflects quality differences, where "quality" refers to any unmeasured attribute of the wafer or transaction that makes one production location more attractive than another. This is the "link-to-show-no-price-change" method in Triplett's (2006) classification of linking methods for matched model indexes. This linking strategy is based upon the assumption that the law-of-one-price holds for quality adjusted units across outlets. As we argue below, there is reason to believe that this assumption does not hold in the semiconductor wafer fabrication industry, potentially leading the standard matched model index to understate the true rate of price decline.

[17] Note that we use price per layer for the results presented here to account for the increased cost of producing more complex wafers containing more layers. As we expect, an index based on price per wafer falls somewhat more slowly, but the qualitative conclusions using price per wafer are the same as those presented here.

As expected, entry and exit of products is a prominent feature of the data. As shown in Table 4.5, 27 cells are new entrants in the 2004-2008 period, and 23 cells are exits. This raises the challenge of estimating price changes for the first and last periods in the series for a large share of the data. However, because our data is high frequency (quarterly), the number of entrants or exits in any given quarter is small, at 2.5 on average. In addition, the weights on these periods are small as new technologies ramp up gradually.

Table 4.6 presents our price index calculations. Column (1) contains the Fisher matched model index just described. We present the quarterly index, yearly averages, and the average yearly change between 2004 and 2008. The index falls by 12.6% per year. As has been known since at least Flamm (1993), Grimm (1998), and more recently Aizcorbe (2002), quality adjustment of prices for semiconductors, and indeed for all high-tech products is critical. In particular, bear in mind (see Table 4.2) that the average price change before adjusting for product composition was slightly positive. The substantial differences across countries points to the necessity of accurate weights by country.

4.4.2 Relaxing the Location as Quality Assumption

Our previous index maintained the assumption that price differences across countries for otherwise identical goods reflect unspecified differences in quality. We now make the opposite assumption: price differences reflect genuine price dispersion across goods of identical quality. Formally, this means that we calculate unit values by technology, averaging across observations from different countries. As a result, substitutions toward low-cost producers will be reflected in the average product price. These two assumptions bracket the truth, which likely lies in between.

We consider this alternative index because the location-as-quality assumption can

lead to biased estimates of price changes under certain circumstances. Consider the convenient example of a situation in which two countries exhibit similar price trends for a given wafer type, but one has a consistently lower price level. Under the approach of Section 4.4.1, any shift toward the lower cost country's foundries will have no effect on the aggregate price index, since the prices decline at the same rate in both countries. The linking procedure implicitly assumes that the savings accrued in shifting supplies are offset by lower quality of the goods being purchased. If, however, the goods are actually identical, then the shift to the lower cost country represents a genuine price drop for the relevant customer. The standard matched model linking approach misses this price drop achieved in switching suppliers, and thus understates the true rate of price decline. This is the so-called "outlet substitution bias" discussed in the Boskin Commission report (Boskin et al. 1996).

To address this, we follow Reinsdorf (1993) and calculate an average price index across outlets.[18] This index is motivated by the opposite quality assumption of the index presented above. If models are very narrowly defined, one can assume that quality for a given model is identical across outlets. In our context, this amounts to assuming that a given process technology is identical across foundries in different countries. If this assumption is correct, then there is no reason to distinguish price relatives by country. Instead, we calculate average prices across countries for each process technology.

$$\bar{P}_i^t = \sum_j w_{ij}^t p_{ij}^t, \tag{4.4}$$

where w is country j's fraction of the total number units of process technology i produced at time t. We then generate price relatives of these average prices for each process technology and use them to generate a Fisher price index as described above.

[18] Ideally, one would be able to directly observe particular buyers substituting between different outlets. Since our data do not include purchaser identifiers, directly observing substitution is not possible.

This approach is able to capture the effect of substitution toward low cost countries as the weights on the lower prices increase with substitution.

If demand for wafers is shifting toward low cost suppliers, and the matched model is missing this substitution effect, we expect to find that the average price index declines more quickly than the matched model index. The results are presented in Column (7) of Table 4.6. The index falls by 13.4% per year, which is 0.8 percentage points faster than the matched model index in Column (1). This result supports the notion that outlet substitution bias causes the standard measure to understate the price declines for wafer fabrication, suggesting an outlet substitution problem no bigger than 0.8 percentage points per year. Note, however, that the scale of quality change over time is much larger, as indicated by the sharp overall price declines.

This result should be interpreted with a number of caveats in mind. Both the law-of-one-price assumption and the alternative assumption of uniform quality across countries are extreme. The data likely reflect both quality differences across countries and some persistent quality-adjusted price differences. Thus, the two approaches bound the true quality-adjusted price change, and the difference between them is an upper bound on the effect of outlet substitution. This discussion raises the question of why quality-adjusted price differences should be able to occur in equilibrium. In the semiconductor fabrication market, a number of observations support the idea that quality-adjusted price differences can persist over time. There have been substantial shifts toward low cost countries. This behavior suggests the presence of quality-adjusted discounts at the low cost countries. Why might that be? Although Reinsdorf (1993) discusses the role of costly information gathering in generating real price dispersion, we think that this explanation is unlikely to hold in a market as concentrated as this one. Rather, we propose an alternative reason for price dispersion

based on the particular characteristics of the wafer fabrication industry.

Very large fixed costs are incurred when getting a production line up to capacity with a given design. Discussions with engineers at a large U.S. fabless firm indicate that it takes a large number of sensitive calibrations to fabricate a particular design on a particular production line. This creates substantial startup cost, such that semiconductor firms are very reluctant even to switch production lines within the same foundry, much less to move a product to a different foundry. This fact, coupled with the nature of new product introduction across countries leads us to a potential explanation for equilibrium price dispersion.

Consider the price plots presented in Figure 4.4. The top panel plots prices by country for a leading edge technology. Taiwan entered the market first, with a high price. Singapore and China each entered later, each at a lower price level. In spite of the increased competition from competitors entering the market, the Taiwanese price continued to decline at a steady rate, maintaining a roughly constant price differential relative to the others. A similar pattern for a more mature process technology is apparent in the bottom panel of Figure 4.4, in which a roughly constant price differential is maintained between the U.S. and Taiwan relative to Singapore and China.

To understand the implications of these observations, consider only Taiwanese and Chinese foundries for simplicity. If a given design requires the newest technology, it will have to be produced in Taiwan. In two years' time, when the Chinese foundry brings the same process technology on line, they charge a lower price in order to win market share away from their Taiwanese competitors. However, the lower wafer price in China does not outweigh the fixed cost of moving the existing products from Taiwan. The Taiwanese foundry can maintain a discretely higher price without

losing its existing business, and only new products using the now year-old technology will go to the lower priced Chinese foundry. The Chinese foundry may adopt the new technology more slowly due to a relative lack of technical expertise or due to U.S. export license restraints on advanced semiconductor fabrication equipment going to China (*U.S., China at odds on fab-gear export* 1998). In any case, the presence of large fixed costs of switching foundries coupled with staggered entry into a given technology makes persistent quality-adjusted price differences across countries possible.

4.4.3 Hedonic Price Index

To check the robustness of our results, we next generate a hedonic price index. Table 4.7 presents some information on the importance of the characteristics we observe. We regress log price per wafer on indicators for foundry location, technological characteristics, contract size, and quarter indicators using the 5,000 observations on contracts for CMOS technology.[19] All of these variables have a noticeable effect on prices and are estimated precisely. Collectively, they account for 88 percent of the variation in wafer prices.

The point estimates on foundry location and process technology appear to be reasonable. Controlling for technology, China has a markedly lower prices than Taiwan, which serves as the baseline case in the regression. Singapore's prices are moderately lower than Taiwan's, while U.S. and European prices are substantially higher. Production using more advanced technologies clearly commands a higher price. Compared to the baseline case of production on 200 mm wafers with 180 nm geometry, production on larger (300 mm) wafers and production with narrower line

[19] As mentioned above, non-CMOS technology is generally used in specialized niche markets. Although we do use non-CMOS prices when calculating industry price indexes, we omit them here for simplicity of exposition. Results for non-CMOS prices, not shown, indicate that location explains little of the variation in pricing, but technological characteristics do play a role.

widths is significantly more expensive. More overall layers per chip, and more metal layers in particular, both proxies for the complexity of the circuitry, also drive up the price. Finally, contracts involving a greater scale of production do appear to draw a volume discount; other things equal, doubling contract size would be expected to reduce wafer costs by 5.5 percent.

Like the matched-model index, the hedonic index also falls rapidly, though the 11 percent average yearly rate of decline is 2 percentage points short of the rate for the matched model.[20] From this we conclude that our baseline results are fairly robust to choice of price index construction methodology. The hedonic specification also controls for characteristics not addressed in the matched model index, which suggest that contract size and the composition of layers contracted does affect pricing. The regression statistics indicate that these features explain over 80 percent of the variation in prices.

4.4.4 Official Indexes

For completeness, this section compares our results to the Bureau of Labor Statistics' price series for imported semiconductors. The BLS' International Price Program (IPP) publishes a price index for Harmonized System code 8542, Electronic integrated circuits. These include microprocessors and memory, the final products of the semiconductor production chain.

IPP draws its sample from Customs lists at the more detailed 10-digit Harmonized System level.[21] For instance, until recently, IPP would draw a sample of establishments whose product(s) are recorded under the just phased-out HS classification 8542.21.80.05 for "unmounted chips, die, and wafers." Price indexes are calculated

[20] Aizcorbe et al. (2003) find a similar result for microprocessors.

[21] This discussion draws on a number of conversations with Sonya Wahi-Miller of the IPP. We are very grateful for the time she spent educating us on the IPP's procedures. Any errors in our characterization of the IPP, however, are our own.

at this more disaggregated level and IPP then aggregates across the price relatives to produce the published index. Unfortunately, this more detailed data is sealed to outside researchers for confidentiality reasons.

Perhaps *the* measurement challenge for IPP is to control for quality improvements in ICs. We do this via a matched model price index that controls for several important performance-related characteristics of wafers. IPP does not necessarily observe as many characteristics of each IC, but it does have a potentially promising way to identify quality improvements. At least some respondents provide BLS staff with their own internal product code assigned to the surveyed item. It is likely that new, higher quality products would receive a new product code. If IPP observes that the product code attached to the surveyed item changes, it will follow up with the respondent to ask what the price of the new product would have been last month so that it can record the true price change for the quality-enhanced good. These follow-ups based on observed changes in firm product codes appear to be one of the principal ways by which IPP adjusts goods, at least in HS 8542, for quality improvements.[22]

The ICs observed by IPP are not directly comparable to the wafers studied in this paper. To see this more clearly, it is useful to recall that we can break up the production of ICs into four stages - design, wafer fabrication, test, and assembly. Our data pertain to the input produced in stage two whereas IPP measures the price of final output shipped at the conclusion of stage four. Nonetheless, it is instructive to ask how average price per wafer compares to the IPP estimate of the price of the finished product.

Table 6 Column (9) presents the IPP index by quarter over the period 2004-

[22]Thus far, we have been unable to obtain information on how often this procedure is generally used in generating the HS 8542 index.

2008. Over this time period, the index falls on average 2.9% per year. Even though this is not directly comparable to our indexes, the discrepancy is quite large. It would imply that the prices in the remainder of the production chain (development, wafer test, and assembly) fall implausibly slowly. Consider, for instance, that recent research has found price declines that approach 40-50 percent per year for finished semiconductors sold in the U.S. (see, among others, Aizcorbe (2002), Table 1). This work suggests that prices at other stages of the production chain, such as test and assembly, actually fall faster than the price of wafer fabrication, which contrasts starkly with the message sent by the IPP series. A critical task for future work is to dig deeper into the sources of these discrepancies. In particular, it seems worthwhile to investigate whether the IPP's follow-up procedure for product code changes does in fact effectively capture key quality improvements.

4.5 Conclusion

Our analysis exploits a rich new data set to calculate constant quality price indexes for processed semiconductor wafers. We calculate a matched model price index, finding that wafer prices fall on average by 12.6% per year. Given that average prices, unadjusted for quality, remain fairly constant over the time period, the sharp yearly price decline demonstrates the importance of careful quality adjustment in this industry. Our results support the conclusion of numerous previous studies that official statistics substantially understate the rate of semiconductor price decline.

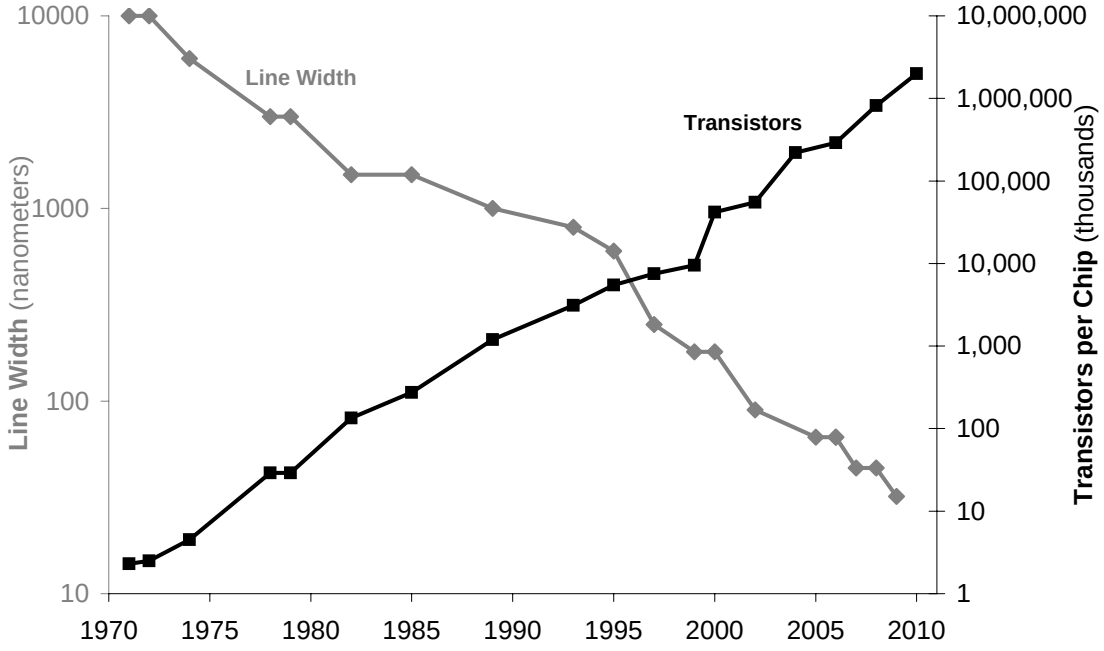
Since our data set includes information on the source country for wafer purchases, we can also measure how geographic changes in sourcing patterns affect price measurement. Our approach is analogous to Reinsdorf's (1993) measurement of retail outlet substitution bias in the CPI. We calculate an average price index that captures

the effects of shifting sourcing patterns toward wafer foundries in low cost countries. Our results imply that the baseline matched model approach understates the yearly price decline by at most 0.8 percentage points.

Although this problem is not overwhelming, particularly in comparison to the much larger issue of quality adjustment in the semiconductor industry, it is suggestive that continued shifts in international sourcing patterns will cause the problem to persist and potentially grow. Our findings here should motivate research into other industries that have seen large shifts in sourcing patterns across countries. Since there are large fixed costs of shifting suppliers in semiconductor production, the finding here may be smaller than the bias in more footloose industries that can substitute quickly in response to smaller price differences. Note however, that future analyses will need to motivate the assumption of persistent quality adjusted price differences across suppliers, as we do here.

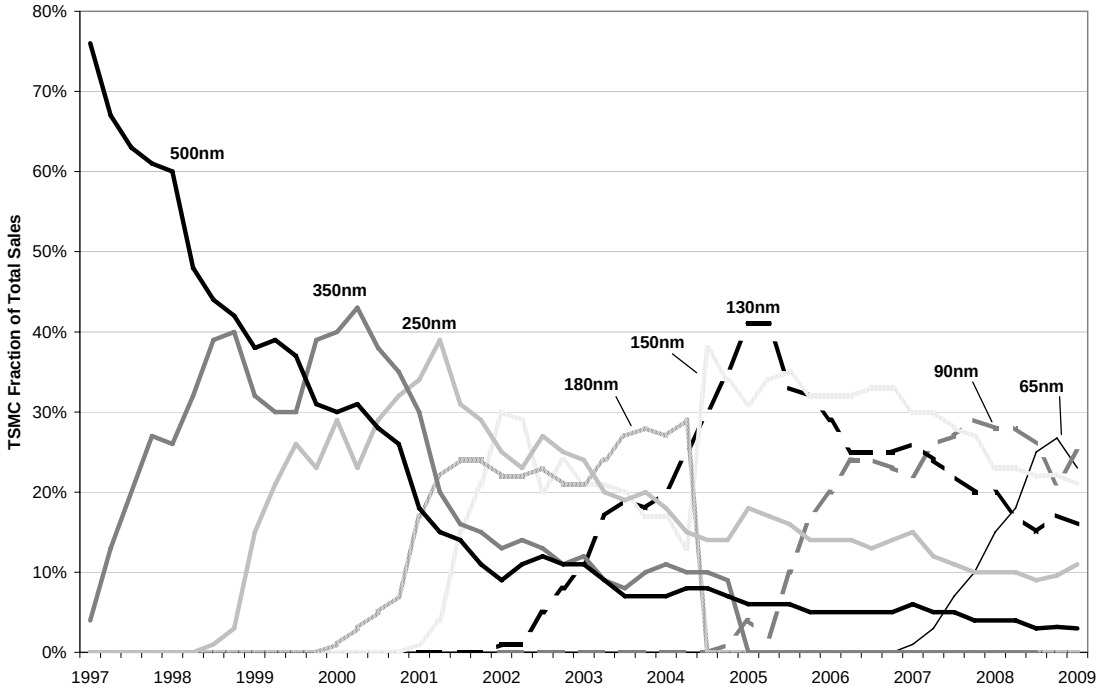
4.6 Figures and Tables

Figure 4.1: Moore's Law — Intel Processors



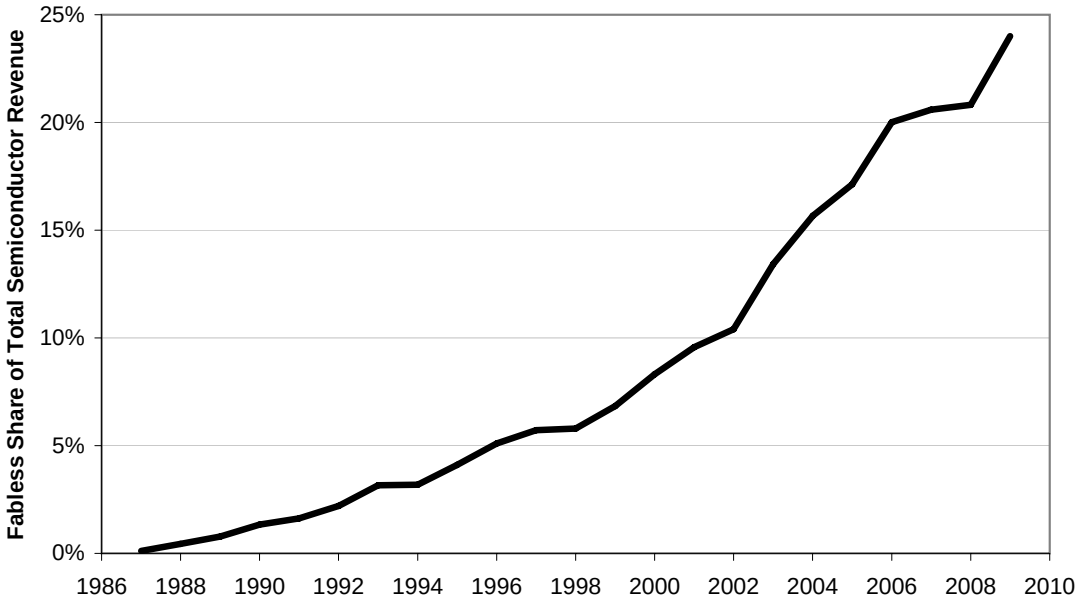
Sources: http://www.intel.com/technology/timeline.pdf, http://www.intel.com/pressroom/kits/quickreffam.htm

Figure 4.2: Technology Cycle - TSMC Sales by line width



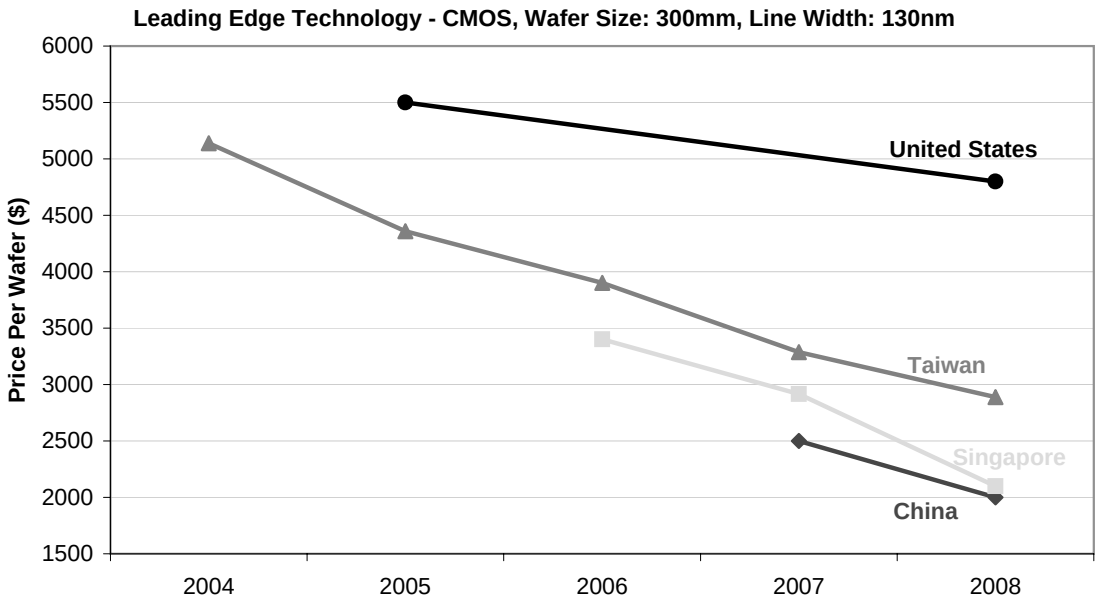
Source: TSMC quarterly reports

Figure 4.3: Growth of the Fabless Business Model



Source: Global Semiconductor Association (GSA) and Semiconductor Industry Association (SIA)

Figure 4.4: Price Differences Across Locations



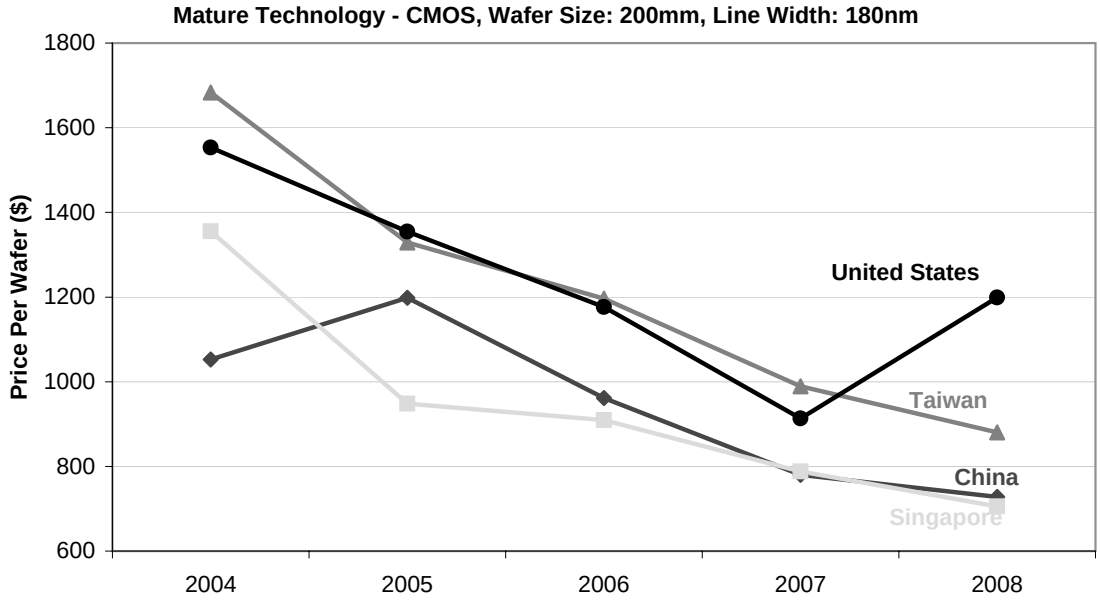


Table 4.1: Dropped Observations

Total observations	7455
Used in analysis	5464
Dropped	1991
Missing:	
foundry location	813
wafers purchased	19
price	19
Other reason:	
engineering run	778
location	499
100mm wafer	3
inconsistent	3

Note: there may be multiple reasons to drop a particular observation

Table 4.2: Descriptive Statistics

			Yearly Means			
	Mean	Std. Dev	2004	2005	2006	2007
Price Per Wafer ($)	1575.40	1145.54	1,576.58	1,609.53	1,502.86	1,545.03
Number of Wafers Contracted	2307	7514	1924	2357	1941	2710
Number of Layers Per Wafer	25.74	7.57	23.25	24.64	25.79	26.64
Metal Layers	4.77	1.81	4.23	4.55	4.75	4.97
Wafer Size						
150 mm or less	0.14	0.35	0.17	0.17	0.15	0.12
200 mm	0.76	0.42	0.80	0.77	0.79	0.76
300 mm	0.10	0.30	0.03	0.06	0.06	0.12
Line Width						
65 nm	0.00	0.06	0.00	0.00	0.00	0.00
90 nm	0.03	0.16	0.00	0.08	0.01	0.03
130 nm	0.23	0.42	0.14	0.18	0.22	0.27
180 nm	0.25	0.43	0.26	0.27	0.26	0.26
250 nm	0.13	0.34	0.13	0.16	0.12	0.12
older vintage	0.36	0.48	0.45	0.38	0.38	0.31
CMOS process	0.92	0.28	0.92	0.92	0.92	0.91

5464 Observations

Source: Authors' calculations based on GSA Wafer Fabrication & Back-End Pricing Survey

Table 4.3: Coverage of Constructed Capacity and Revenue

	Wafer Start Capacity (1,000 Wafers per Week)		Revenue (US $ Billion)	
	SICAS	Constructed	iSuppli	Constructed
2004	194	123	16.6	9.1
2005	252	139	16.3	9.0
2006	285	151	19.5	9.6
2007	288	172	19.7	9.8
2008	297	188	20.1	9.9

Source: SICAS, iSuppli, and author's calculations from sources described in text

Table 4.4: Foundry Revenue and Share for Major Offshore Locations

	Revenue ($million)	Taiwan	China	Singapore
2004	7232	66.0%	19.7%	14.3%
2005	8517	61.7%	20.4%	17.8%
2006	8549	62.0%	20.1%	17.9%
2007	8668	60.3%	21.6%	18.1%
2008	8432	59.8%	21.7%	18.5%

Note: Includes pure-play foundries only.

Source: Authors' calculations based on data from GSA, Gartner, and company reports

Table 4.5: Entry and Exit Statistics, CMOS Process

country technology cells with data	74
ave. no. quarterly prices per cell	10.18
new entrants	27
exits	23
cells with entry or exit	38
ave. quarters with missing prices	5.375

Table 4.6: Price Index Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Fisher Matched-Model Indexes						Average	Hedonic	BLS IPP
Quarter	Overall	Taiwan	China	Singapore	USA	Europe	Price Index	Index	HS 8542
2004Q1	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
2004Q2	101.5	101.7	99.9	102.7	97.5	108.5	100.7	99.5	98.3
2004Q3	99.6	103.2	90.1	101.7	97.2	94.6	98.4	97.7	97.1
2004Q4	93.5	95.1	84.3	102.1	95.5	89.1	89.5	91.3	95.9
2005Q1	91.3	86.9	100.5	101.5	93.0	89.5	87.7	87.4	95.5
2005Q2	83.5	76.9	95.2	94.1	95.2	85.1	79.1	87.3	95.1
2005Q3	81.7	79.5	85.5	88.7	80.0	86.8	79.5	83.8	93.9
2005Q4	82.0	79.2	90.6	85.8	79.3	92.1	77.8	82.7	93.5
2006Q1	76.4	73.6	83.5	82.0	69.4	87.2	72.8	78.4	94.0
2006Q2	74.4	71.6	77.8	84.2	70.8	82.0	70.4	74.1	93.8
2006Q3	72.4	69.4	78.0	80.8	66.4	82.0	68.7	73.6	94.6
2006Q4	69.6	65.9	78.6	76.4	64.1	82.1	66.3	71.0	95.3
2007Q1	70.3	67.1	77.7	75.7	65.6	87.6	66.9	69.2	93.3
2007Q2	67.9	63.3	77.4	77.1	59.1	90.0	64.8	67.6	88.8
2007Q3	62.8	58.7	67.2	74.8	56.0	88.4	59.7	65.3	90.0
2007Q4	59.6	55.5	65.3	70.1	52.2	84.1	56.5	64.5	90.3
2008Q1	60.4	55.7	66.3	71.7	58.2	83.7	57.3	65.0	88.5
2008Q2	57.1	51.9	63.9	68.2	57.1	83.3	54.3	61.9	87.5
2008Q3	58.2	52.5	68.2	65.0	69.2	85.3	55.3	59.6	85.8
2008Q4	54.2	49.2	63.1	59.7	63.4	82.9	51.4	59.7	85.6
Year									
2004	98.6	100.0	93.6	101.6	97.6	98.1	97.2	97.1	97.8
2005	84.6	80.6	93.0	92.5	86.9	88.4	81.0	85.3	94.5
2006	73.2	70.1	79.5	80.9	67.7	83.3	69.5	74.3	94.4
2007	65.2	61.2	71.9	74.5	58.2	87.5	62.0	66.6	90.6
2008	57.5	52.3	65.4	66.2	62.0	83.8	54.6	61.6	86.9
Avg. Yearly Change '04-'08	-12.6%	-14.9%	-8.6%	-10.2%	-10.7%	-3.9%	-13.4%	-10.8%	-2.9%

Table 4.7: Descriptive Wafer Price Regression Results

dependent variable: log of price per wafer

Variable	Coefficient	Std. Err.	t-Stat
Foundry Location			
China	-0.272	0.019	-14.59
United States	0.218	0.014	15.58
Europe	0.119	0.018	6.54
Singapore	-0.062	0.012	-5.30
Wafer Size			
150 mm	-0.344	0.015	-22.20
300 mm	0.645	0.014	47.68
Line Width			
≥ 1000 nm	-0.696	0.038	-18.24
800 nm	-0.353	0.027	-13.31
600 nm	-0.358	0.022	-16.12
450 nm	-0.355	0.019	-18.35
350 nm	-0.194	0.013	-14.59
250 nm	-0.092	0.012	-7.74
130 nm	0.306	0.012	26.31
90 nm	0.511	0.025	20.19
65 nm	0.737	0.050	14.63
layers per wafer	0.012	0.001	13.83
no. metal layers	0.057	0.004	14.30
log wafers contracted	-0.055	0.002	-32.92
constant	6.743	0.030	223.47
R-squared	0.8773		
Observations	5000		

Specification also includes quarterly indicator variables
non-CMOS production not included
Baseline case (omitted category) is Taiwan, 200mm, 180nm

CHAPTER V

Conclusion

As described in the introduction, the three essays comprising this dissertation are independent and span the fields of trade and labor economics. The first essay examines the effects of trade liberalization on local labor market outcomes and workers' migration patterns. The findings demonstrate a link between trade and internal migration that had been absent in theoretical and empirical examinations of the effects of trade liberalization on labor markets. The second essay argues that standard cost function estimates overstate the effect of capital-skill complementarity, a potentially important driver of increased income inequality. The analysis demonstrates an alternative method to correctly measure the effects of complementarity that can be used in future examinations of the drivers of inequality. The third essay examines the implications of global production sharing for measuring the price of semiconductors, with important implications for measuring productivity when inputs to final goods are produced across various countries.

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