Inequality and Prices: Does China Benefit the Poor in America?*

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Abstract

Over the past three decades there has been a spectacular rise in income inequality as measured by official statistics. In this paper we revisit the distributional consequences of increased imports from China by looking at the compositional differences in the basket of goods consumed by the poor and the rich in America. Using household data on non-durable consumption between 1994 and 2005 we document that much of the rise of income inequality has been offset by a relative decline in the price index of the poor. By relaxing the standard assumptions underlying the representative agent framework we find that inflation for households in the lowest tenth percentile of income has been 6 percentage points smaller than inflation for the upper tenth percentile over this period. The lower inflation at low income levels can be explained by three factors: 1) The poor consume a higher share of non-durable goods —whose prices have fallen relative to services over this period; 2) the prices of the set of non-durable goods consumed by the poor has fallen relative to that of the rich; and 3) a higher proportion of the new goods are purchased by the poor. We examine the role played by Chinese exports in explaining the lower inflation of the poor. Since Chinese exports are concentrated in low-quality non-durable products that are heavily purchased by poorer Americans, we find that about one third of the relative price drops faced by the poor are associated with rising Chinese imports.

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I. Introduction

Over the last three decades official measures of US income inequality have risen substantially. Alongside this rise in inequality, there has been a quadrupling of US trade with developing countries. While most studies have focused on wage or income inequality (see Feenstra and Hanson (2001) and Goldin and Katz (2007) for recent surveys), little attention has been paid to the role played by inflation differentials between the consumption baskets of the rich and poor. This is particularly surprising given that developing countries produce relatively low quality goods that are disproportionately consumed by lower income households, and that the price of goods relative to services have been falling substantially over this period. In this paper we relax a standard assumption underlying the calculation of conventional price indexes – that rich and poor consume a common basket of goods– and re-examine the evidence on official measures of inequality. Using detailed household consumption data between 1994 and 2005, we find that over this period the rise in inequality has been less than one third that implied by official statistics. Moreover, by matching detailed US trade data with consumption patterns of households of different income groups in the US, we argue that the rise of Chinese trade has helped reduce the relative price index of the poor by around 0.3 percentage points per year. This effect alone can offset around 30 percent of the rise in official inequality we have seen over this period.

The lower inflation rates we find at low income levels can be explained by three factors. First, the poor consume a higher share of non-durable goods than the rich and non-durable goods inflation has been 10 percentage points smaller than service inflation during the 1994 – 2005 period. In particular, we show that the poor's consumption share of non-durable goods is 12 percentage points larger than that of the rich. Second, we document that the prices of the basket of non-durable goods consumed by the poor have fallen relative to the basket consumed by the rich. The prices of the lower quality non-durable products consumed by the poor have fallen by 5 percentage points relative to the price index of the rich over this period. Finally, we document that the number of non-durable goods purchased by the typical poor household in the US has increased by 10 percent between 1998 and 2005, while there has been no change in the pattern

observed for rich households. This increased access to new goods has further reduced the relative cost-of-living of poor relative to rich households.

We examine the role played by Chinese exports in explaining the lower inflation of the poor. We extend a standard Ricardian model of trade and wages to allow consumers to differ in the types of goods they consume and for countries that produce goods of different qualities. We find that while the overlap in production capabilities between two countries is small, increased trade with unskilled labor abundant countries like China can make unskilled workers in the US better off. The reason is that while the expansion of trade with low wage countries triggers a fall in relative wages for the unskilled in the US, it also leads to a fall in the price of goods that are heavily consumed by the poor. We show that this beneficial price effect can potentially more than offset the standard negative relative wage effect.

Our starting point to examine the impact of US imports from China on US retail prices is to generate a concordance between 10-digit HTS final consumption trade categories and non-durable goods categories from ACNielsen's Homescan panel called "modules". With this concordance we can document three key facts that suggest that the mechanism underlying the model is likely to be important in the data: 1) The rise in Chinese exports have been heavily concentrated in low quality products; 2) Lower income households consume a higher share of non-durable goods and in particular of low-quality products; 3) In the modules where the share of Chinese exports to the US have increased the most, US prices have fallen the most. The semi-elasticity between log price changes and share changes is estimated at around -0.4. The magnitude of this semi-elasticity is larger for the goods consumed by the poor and for the set of non-durable goods outside food.

These new facts have important implications for the measurement of inequality and the debate on trade and inequality. First, ratios of the 90^{th} to 10^{th} percentiles of the US income distribution have grown by 6 percent from 1994 to 2005, roughly a third of the total rise in inequality since 1984.[1] When income-group specific inflation rates are used to estimate the change in inequality, $90^{th}/10^{th}$ ratios have risen only 2 percent in this period. Moreover, if inflation rates are corrected for new-goods bias using the methodology in Broda and Weinstein

[1] I use 1984 as a benchmark for this comparison because the BLS data on disaggregate prices on non-durable and service inflation starts in 1984. Between 1972 and 1984, the $90^{th}/10^{th}$ ratio of the US income distribution increased an additional 6 percent.

(2007) we find that inequality has been unchanged since 1994.[2] Using the impact of China on US non-durable consumer prices and given that the share of Chinese goods in total US imports have risen from 6 to 17 percent over the 1994 – 2005 period we estimate that the price effects of the increased imports from China alone can offset around 30 percent of the rise of conventional inequality measures over this period.

II. Data Description

II. A. Overview

The paper uses detailed household consumption data on a large set of non-durable goods. The data is part of the Homescan database, collected by ACNielsen in the United States, that records price and quantities of purchases of thousands of households. ACNielsen provides Universal Product Code (UPC or barcodes) scanners to a demographically representative sample of households. Households then scan in every purchase they make. We use two extracts of the complete Homescan database that provides us with a vast array of goods with barcodes. The majority of these goods are non-durable products sold in groceries, drugs, and mass merchandise stores. Moreover, we have access to the household level data which contains information on the barcoded goods purchased by each household combined with a wealth of household characteristics.

We refer to the first extract of the Homescan data as our "Non-Durable" database. For this extract we have price and quantity data on every UPC purchase by a sample of 55,000 households for every quarter in 1994, and every quarter between 1999:Q1 and 2003:Q4. In addition, we have detailed information about the purchases and characteristics of a sample of 3000 households in 2003:Q4. As we explain in the next section, we combine this information to compute income specific price indices over time. Table 1A summarizes this database in terms of the number of households, number of UPCs and modules (i.e., ACNielsen's classifications of different UPCs into broader product categories). Examples of the types of non-food modules included in this database include "cosmetics", "toys and sporting goods", "house ware appliances", "cookware", and "wrapping materials and bags".

[2] Using conservative assumptions about the behavior of relative inflation outside our sample period, we find that differential inflation rates offset almost two thirds of the increase in official measures of inequality since 1984.

The second extract we use includes detailed information on the food purchases and demographic characteristics of a large subsample of household included in the Homescan database between 1999 and 2005. We refer to this extract as the "Food" database. In this extract, we have household level data on every purchase in around 60 percent of the modules included in the complete data.[3] Table 1B provides a summary statistics of the number of UPCs, modules and households included in this database. The data is divided into four broad categories: dairy, dry grocery, frozen and processed foods, and random weight products. We obtained the detailed household information on approximately 8,000 households from 1998 to 2003, and around 38,000 for 2004 and 2005. In 2005 this extract includes 640 modules and over 380,000 UPCs, most of which are classified under the dry grocery category.

A number of crucial characteristics of the household are included in this database. In particular, the households' income, the head of household's occupation and education level are included. The distribution of households by income group and female household head education level are provided in Figure 2A and 2B. Since we rely heavily on the information of households that are among the poorest and richest in our data, it is useful to examine how well our data represents the true population. According to the US Census Bureau the cutoffs for the 10^{th} and 20^{th} percentile income distribution are approximately $12,000 and $20,000, respectively.[4] Around 8 percent of our sample of households falls below the $15,000 threshold, and around 14 percent of the households have income less than $20,000. This implies that in 2005 we have detailed data on over 5,000 households which are in the lowest deciles of the income distribution.[5,6]

These datasets are ideal for understanding how prices evolve for households of different income groups. First, they include a long time series of price and quantity data for a large sample of non-durable consumption goods consumed by each income group. This is an advantage relative to current studies that do not observe the specific prices that households pay for each

[3] Examples of the types of food modules "soft drinks non-carbonated", "sugar, sweeteners", "seafood" and "prepared, ready to eat food".
[4] U.S. Census Bureau, Current Population Survey, 1968 to 2007 Annual Social and Economic Supplements
[5] The U.S. Census Bureau selects a sample of approximately 7,100 households to build the CEX survey.
[6] While we have little information on response rates by different income groups, Nevo et al (2008) suggest that the coverage of good for all income groups, while respond rates and measurement error is larger at the higher income groups. We take some comfort in that we observe purchases for a large number of households in the upper decile of the income distribution.

item. Our data circumvents these limitations by using data directly collected by a representative set of households. A second distinctive feature of our database is that we can identify the different types of goods purchased by each income group. While official statistics are based on the basket of a representative agent, these data allow us to measure the differences in consumption baskets across income groups. This is information that is not observed by the BLS or other statistical agencies. A third crucial characteristic of this database is that along with prices of each of the products, quantities of the same products are also collected at the same frequency. This implies that we can have consumption weights varying by income groups. This allows us to be very precise when analyzing income group specific price indexes.

We also use 10-digit Harmonized Tariff System (HTS) trade data for the period between 1991 and 2005 (Feenstra (1996) and Feenstra et al. (2002)). In particular, we use the HTS 10-digit data with individual records for each month, port of entry, port of unloading, method of transportation and tariff program. This implies that for many products and exporting countries there are multiple observations of value and quantity in the raw data. For future reference we will refer to each of these separate entries as a particular "shipment". In Table 2 we report the total number of HTS categories between 1972 and 2005. In 2005, there were around 16,800 different HTS categories coming from 228 different countries. In that same year, China exported in around 75 percent of all possible HTS categories. In particular, in each category for each 10-digit product coming from China in 2005 we have on average 77 different shipments.

Before proceeding further, it is worth taking a moment to review precisely how these databases where matched. Since the ACNielsen's module categories involves only final consumption products, we only focus on the HTS categories that are classified as final consumption, or around one third of the total HTS products. Using the detailed HTS product descriptions we matched each of these categories to the detailed module description provided by ACNielsen. This provided us with a concordance between 4248 different final consumption HTS categories with the approximately 1100 ACNielsen module categories. Table 3 provides 25 representative examples of the level of detail of this concordance.

II. B. Stylized Facts

In this sub-section we describe the extent and nature of Chinese exports to the U.S. economy and how the consumption patterns of Americans differ across income groups. We present several facts that are crucial in our re-examination of the impact of Chinese trade in US income inequality.

II.B.1. The Extent and Type of Chinese Exports to the US

Figure 1 shows the sharp rise of Chinese exports to the US in the last 35 years.[7] In particular, it shows that most of the rise has been concentrated since 1990. The share of Chinese imports on total US imports increased from 3 percent in 1990 to over 18 percent in 2006. While this fact has been widely documented, a feature of the data that has been less emphasized is the nature of the Chinese goods being exported to the US.[8] In this section we describe the export of Chinese products in terms of two dimensions that are particularly relevant for this study. First we decompose Chinese export flows by capital-labor (K/L) intensity. This is important in the context of inequality as trade has detrimental effects on income inequality in the US mostly if it involves trade in labor intensive industries. The second dimension in which we decompose Chinese exports is in terms of the quality of individual products in each HTS category. This is of special interest as we argue in the next sub-section that the poor buy a higher fraction of low-quality products. We describe next how we perform such decompositions.

As is standard in the literature we matched HTS 10-digit codes with the 4-digit SIC production data from the NBER-CES Manufacturing Industry Database to determine the K/L ratio of each HTS.[9] In particular, we calculated the share of Chinese imports in overall US imports in each of 10 different K/L bins.

We also divided the trade data into 10 different unit-value bins. A useful feature of the product-level US trade data is the inclusion of both value and quantity information for most

[7] This figure excludes Hong Kong. Including Hong Kong, the share of China plus Hong Kong was 2 percent in 1972, 3.4 percent in 1984 and 20 percent in 2005.

[8] An exception is Schott (2008).

[9] This database is a joint effort between the National Bureau of Economic Research (NBER) and U.S. Census Bureau's Center for Economic Studies (CES), containing annual industry-level data on output, employment, payroll and other input costs, investment, capital stocks, TFP, and various industry-specific price indexes. The database covers all 4-digit manufacturing industries from 1958-1996, in two versions: 1987 SIC codes (459 industries) and 1972 SIC codes (448 industries).

individual shipments (HTS categories from different countries, months, port of entry, port of unloading, method of transportation and tariff program). This allows us to calculate unit values as a measure of price. For simplicity, and given the level of detail of the shipment trade data, we proxy the quality of each shipment in terms of its unit value relative to the unit value of all shipments in that particular HTS category. We compute the unit value of HTS *h* from shipment *s* from country *c*, uv_{hsc} by dividing the free-on-board (fob) import value by import quantity, $uv_{hsc} = \frac{v_{hsc}}{q_{hsc}}$.[10] For each HTS we divide shipments into different unit-value deciles – 10 percent of each HTS product by value falls into each decile. In particular, we are interested in computing the share of Chinese exports in each decile across all HTS categories. For instance, in HTS 0307490010, Squid Frozen fillets, the typical unit value is $3.2 per kg, while the lowest decile involves shipments with unit values below $1 per kg and the highest decile includes shipments with unit value above $6.3 per kg.

Figures 3A shows the decomposition of Chinese exports by K/L ratio deciles and unit-value deciles in 1991. Each bin reflects the share of Chinese exports in total US imports in that particular bin. For instance, in the bin (1,1), i.e. the lowest decile of K/L ratios and unit-values, the share of Chinese exports in the total imports of the US in that bin was around 20 percent. By construction, the average share in all bins is similar to the share of Chinese exports in total US imports.[11] The graph shows a dramatic pattern of Chinese exports in 1991. China exports to the US are highly skewed towards low capital intensive products and low unit value products.

Figure 3B shows the same decomposition in 2005. While the increased sophistication of exports from China to the US is apparent in the figure, most of Chinese products are still concentrated in low unit value and low capital intensity bins. Note also how the average share of China increased substantially over this period. More importantly for the results in the following section, Figure 4A shows the change in the share of Chinese Exports in total US imports in each

[10] It is important to note that the unit values are measured with error. A study by the US General Accounting Office (1995), for example, identified classification error and underlying product heterogeneity as two major sources of unit value error in an in-depth analysis of eight products. Of course, identifying potential heterogeneity within product categories is a goal of this section. Moreover, unit values are known to increase with transportation costs (Hummels and Skiba, 2004). This relationship has been interpreted as capturing Alchian and Allen's (1964) idea that firms have an incentive to ship their highest quality goods to their furthest customers when facing per unit transport costs. We are not controlling for these effects in the current version of the tables.

[11] The reason why it is not exactly this share is that value of imports in each bin is not constrained to be the same.

bin. Between 1991 and 2005, low unit value bins experienced the highest growth. While the pattern of growth in low-quality products is clear in the graph, in the last 15 years the increase in Chinese growth is not so clearly concentrated in low capital intensive bins.

Interestingly, Figure 4B shows a similar pattern for the change in the share of the number of Chinese varieties in the total number of imported varieties by the US in each bin. For instance, in 1991 China on average exported around 7 different HTS goods in each K/L ratio and quality bin. By 2005, China exported on average around 60 different HTS per bin. This represents a dramatic rise in the importance of China in the extensive margin of each bin. The pattern that emerges from figure 4B suggests an even more skewed behavior than that in 4A. The increase in the number of Chinese varieties as a share of total varieties per bin has been particularly high in low quality bins.

II.B.2. Consumption Baskets by Income Group

In this section we document 3 facts that highlight the differences in the pattern of non-durables consumption across different income groups. We first report how the basket of non-durable goods consumed differs systematically by income group. In particular, we show that the poor systematically consume lower quality products across all modules than the rich. Second, we show that over the sample period the poor have benefitted from an increased access to goods relative to that of the rich. Finally, we document how the share of non-durable consumption in total consumption is higher for the poor than the rich.

We can understand the differences in the quality of goods consumed by different income groups by examining the unit-values of the products consumed in each module by each income group. A useful feature of the ACNielsen Food data is that in addition to the price and quantity of each UPC consumed by different income groups, it provides detailed information on the size of each UPC. This allows us to compute unit values for each module – size pair. For instance, within the module "Milk", there are UPCs sold under many different sizes (e.g., 16 oz, 32 oz and 64 oz). The lowest income groups consume UPCs within Milk – 16oz that are 25 percent cheaper than those consumed by the households in the highest decile of the income distribution. In particular, richer household consume a much higher fraction of organic milk. Figure 5 reports the

average unit value paid by each income group relative to the maximum unit value for each module – size pair. Formally this implies computing the following statistic:

$$(1) \qquad rel\_uv_{m,size,I} = \frac{\overline{uv}_{m,size,I}}{\max_Z(\overline{uv}_{m,size,Z})}$$

where $\overline{uv}_{m,size,I} = mean_u\left(uv_{u,m,size,I}\right)$, u is UPC code and "I" is a household's income group. The solid line in this figure shows that households with the lowest incomes consume on average products with unit values that are around 20 percent smaller than those in the highest income groups. That is, the highest income groups have a relative unit value close to 1, or close to the maximum unit value in each module – size pair. The poor, instead, consume cheaper UPCs in each module – size pair. The average unit value for the poor is 80 percent that of the maximum unit value in the pair.

While this evidence is suggestive that the poor consume UPCs that are of lower quality than those consumed by the rich, an obvious critique of the evidence is that the poor may just be consuming the same UPCs as the rich at a lower price (e.g., Broda and Weinstein (2008) and Broda and Hurst (2008)). To show that this is not driving the results underlying the different unit values consumed by income group we report the prices paid by income group for the UPCs that are purchased by all income groups. In particular, the dotted line in figure 5 reports the average price paid by different income groups relative to the maximum price of that UPC. The slope is much flatter than that of the solid line, suggesting that the vast majority of the decline in unit values paid by the poor is indicative of lower quality products rather than lower prices paid for identical products. Combined with the facts found in previous sections (i.e., that China exports growth has been primarily concentrated in low quality goods), this is an important building block for some results of this paper. Since the poor consume lower quality products, the impact of the larger access and lower prices of Chinese products will disproportionately influence the poor.

Interestingly, we also observe a very different evolution of the number of UPCs consumed across income groups. Since the number of households in each income group differs over time we compute the relative number of UPCs per household for each income group as

$$(2) \qquad rel\_numperhh_{I,t} = \frac{numperhh_{I,t}}{numperhh_{100K+,t}}$$

$numperhh_{I,t}$ is the number of UPCs per household in income group "*I*" in period *t* and $numperhh_{100K+,t}$ is the number of UPCs per household in the highest income group in period *t* (i.e., income larger than $100,000). Figure 6 shows the percent change in the relative number of UPCs per household by income group, $d\ln(rel\_numperhh_I)_{1999-2005}$. The figure shows a dramatic pattern. Households with incomes below $13,000 have been experiencing large increases in the number of UPCs they purchase relative to the richest households. These households have on average seen an increase of 10 percent on average in the relative numbers of UPCs they purchase. As we will show in the coming section this is a feature of the data that is missed by conventional prices indexes.

The third fact that we document in this section is how the share of non-durable consumption differs markedly across income groups. It is well-known that the share of non-durable consumption has fallen substantially over time as per-capita consumption rises. Figure 7A shows the pattern in the time-series data for the US between 1929 and 2006 from NIPA tables. The share of non-durable consumption (round symbols) has been as high as 60 percent in the 1930s and has fallen to below 30 percent in 2006. The decline of the share of non-durable consumption we observe in the time-series evidence is the mirror image of the share of services (triangle symbols) in the economy. This is corroborated by the fact that the share of durable goods (the only missing group, x symbols), has been essentially flat over the last 80 years.

Figure 7B shows a similar behavior in the cross-section of households in the US in 2005 using data from the Census Consumer Expenditure Survey. The poorest households (less than $5K of income) have a share of non-durables in consumption as high as 40 percent, while the richest households in the ACNielsen household survey (more than $100K) have shares of less than 30 percent. This sharp difference in the shares of non-durable consumption across income groups will be important when determining the impact of lower non-durable inflation in each group's total CPI. Again, in the cross-section the share of services is the mirror image of the share of non-durable goods.

III. Calculating Inflation Rates by Income Groups

In Appendix B we present a model that highlights the importance of considering income specific price indexes to examine the role played by Chinese exports in explaining income inequality. We show that increased trade with unskilled labor abundant countries like China can make unskilled workers in the US better off. The reason is that while the expansion of trade with low wage countries triggers a fall in relative wages for the unskilled in the US, it also leads to a fall in the price of goods that are heavily consumed by the poor.

Since the model in the appendix is too stylized to be used for calculating price indexes, in this section we derive exact price indexes by income groups based on a richer utility framework than the one used in the appendix. This differs from conventional or official CPI measures that are based on a representative household in the economy. [12]

We build income-group specific price indexes by relaxing three standard assumptions underlying the representative agent framework. First, we allow the type of non-durable goods consumed by the poor to differ from those consumed by the rich. Second, we allow the share of non-durable consumption in total consumption to differ across income groups. Finally, we allow the introduction of new goods to affect the calculation of the cost-of-living index, and we permit the access to goods to differ by income groups.

We now write down these restrictions formally by extending Broda and Weinstein's (2007) derivation of an exact aggregate CES price index for a representative agent. The first step towards deriving an aggregate exact price index is defining a utility function over all goods available for consumption. Since we do not focus on understanding the reasons behind the differences in consumption behavior across income groups it is simplest to build consumer price indexes based on utility functions where the basket of goods and expenditure shares vary exogenously across income groups.[13] Suppose that the preferences of a particular household from income group *I* can be denoted by a two-level utility function[14]

[12] Statistical offices around the world compute changes in consumer prices for an "average" person in the economy. In the US, the BLS conducts "Point of Purchase Surveys" to assess where people are buying their products. These surveys use demographic and socioeconomic information that allows BLS to monitor how well the selected interviewers represent the overall population.

[13] Of course an alternative way to proceed is to have the same utility function across income groups, but allowing for non-homothetic preferences.

[14] In the empirical section we will divide durable goods into cars and other durables consumption, and services into housing and non-housing services.

$$(3) \qquad \Omega_{It} = \left(\left(\sum_{m \in M_t} ND_{mIt}^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}} \right)^{\alpha_I} D_{It}^{\beta_I} S_{It}^{1-\alpha_I-\beta_I} \; ; \gamma > 1$$

where ND_{mIt} is the sub-utility derived from the consumption of the non-durable goods in module *m* by income group *I* at time *t*, γ denotes the elasticity of substitution among goods in different modules, and D_{It} and S_{It} are composites for durable goods and services consumption, respectively; $M_t \subset \{1,...,N_t\}$ is the set of modules available in period *t*. The set *M* is fixed over time ($M_t = M \; \forall t$) and all income groups consume positive amounts in all modules, so γ plays no role in the analysis that follows.

The Cobb-Douglas assumption between the aggregate non-durable goods and the other goods and services in consumption allows us to define a utility-based non-durable price index that is separable from the overall consumer price index. A particularly useful form of ND_{mIt} is the *non-symmetrical* CES function, which can be represented by

$$(4) \qquad ND_{mIt} = \left(\sum_{u \in U_{mt}} d_{umIt}^{\frac{1}{\sigma_m}} \left(c_{umIt} \right)^{\frac{\sigma_m - 1}{\sigma_m}} \right)^{\frac{\sigma_m}{\sigma_m - 1}} \; ; \sigma_m > 1 \; \forall m \in M_t$$

where c_{umIt} is the consumption of UPC *u* of module *m* by income group *I* in period *t*, σ_m is the elasticity of substitution among varieties of good *m*, which is assumed to exceed unity[15]; U_{mt} is the set of all possible UPCs of module *m* in period *t*; and d_{umIt} denotes a taste or quality parameter of income group *I* for good *u* of module *m* in period *t*. For future reference, each income group will consume a different set of goods, i.e. $U_{mIt} \subset U_{mt}$, and the set of UPCs consumed in both periods *t* and *t-1* by income group *I* is given by $U_{mI} \subset U_m = U_{mt} \cap U_{mt-1}$ where U_m is the set of all common UPCs between periods.

If the set of UPCs available for each group is fixed over time, Sato (1976) and Vartia (1976) have derived the exact price index in the case of the CES utility function. In the case

[15] Note that elasticities of substitution are not allowed to vary across income groups. We will relax this assumption as a robustness check.

where goods and shares of particular UPCs are allowed to vary by income group, the "common goods" exact price index is defined as follows,

$$\pi_{mI} = \prod_{u \in U_{mI}} \left(\frac{p_{umIt}}{p_{umIt-1}} \right)^{w_{umIt}} \tag{5}$$

This is the geometric mean of the price changes of individual UPCs that belong to the set $U_{mI} \subset U_m = U_{mt} \cap U_{mt-1}$, where the weights are ideal log-change weights.[16] These weights are computed using expenditure shares of each income group, s_{umI}, in the two periods, as follows:

$$s_{umIt} = \frac{p_{umIt} c_{umIt}}{\sum_{u \in U_{mI}} p_{umIt} c_{umIt}} \tag{6}$$

$$w_{umIt} = \frac{\frac{s_{umIt} - s_{umIt-1}}{\ln s_{umIt} - \ln s_{umIt-1}}}{\sum_{u \in U_{mI}} \left(\frac{s_{umIt} - s_{umIt-1}}{\ln s_{umIt} - \ln s_{umIt-1}} \right)} \tag{7}$$

The numerator of (7) is the difference in shares over time divided by the difference in logarithmic shares over time.

The introduction of new goods implies that a true cost-of-living index will differ from the common-goods exact price index defined in (5). Feenstra (1994) showed how to modify this common-goods exact price index for the case of different, but overlapping, sets of varieties in the two periods. Suppose that there is a set of UPCs $U_{mI} \neq \varnothing$ that are available in both periods, and for which the taste parameters are constant. Extending the work of Broda and Weinstein (2006) we can derive different cost-of-living indexes by income group from the utility structure allowing for product creation and destruction in each module in each income group:

$$COLI_{mI} = \pi_{mI} \times \left(\frac{s^c_{mIt}}{s^c_{mIt-1}} \right)^{\frac{1}{\sigma_m - 1}}, \tag{8}$$

[16] As explained in Sato (1976), a price index P that is dual to a quantum index, Q, in the sense that $PQ = E$ and shares an identical weighting formula with Q is defined as "ideal". Fischer (1922) was the first to use the term ideal to characterize a price index. He noted that the geometric mean of the Paasche and Laspayres indices are ideal.

$$\text{where } s^{c}_{mI,t} = \frac{\sum_{u \in U_{mI}} p_{umIt} c_{umIt}}{\sum_{u \in U_{mIt}} p_{umIt} c_{umIt}}.$$

$COLI_{mI}$ is the cost-of-living index (or exact price index) for module *m* adjusted for new-goods bias between periods *t* and *t* – 1 of income group *I*, and $s^{c}_{mI,t}$ is the share of common UPCs in module *m* consumed by income group *I* to the total consumption of group *I* in module *m*.

Given the CES nature of the aggregator over all different non-durable modules, we can again apply the Sato and Vartia formula to aggregate the common exact price indexes or π_{mI} s of different modules. This defines the "common" goods aggregate exact price index for all non-durable modules to be:

(9) $$\pi_{ND,I}\left(U_I\right) = \prod_{m \in M} \pi_{mI}\left(U_{mI}\right)^{w_{mI}}$$

where the weights are ideal-log change expenditure weights on total non-durable consumption defined in a similar way to (7), and $U_I = \bigcup_{m \in M} U_{mI}$.

If we explicitly allow for product turnover in each module, we can aggregate over all modules and obtain the following expression for the relationship between the conventional inflation measures and changes in the cost-of-living index:

(10) $$COLI_I = \pi^{\alpha_I^{ND}}_{ND,I} \times \prod\nolimits_{m \in M} \left(\frac{s^{c}_{mIt}}{s^{c}_{mIt-1}} \right)^{\frac{\alpha_I^{ND} w_{mI}}{\sigma_m - 1}} \times \pi_D^{\alpha_I^{D}} \times \pi_S^{\alpha_I^{S}},$$

Overall inflation adjusted for new-goods bias is comprised of three different terms: 1) $\pi^{\alpha_I^{ND}}_{ND,I}$ is the "common-goods" exact price index for income group *I* for non-durables modules; 2)) $\pi_D^{\alpha_I^{D}}$ is the "common-goods" exact price index for all income groups for durables modules and $\pi_S^{\alpha_I^{S}}$ is the "common-goods" exact price index for all income groups for all services, which is restricted to be the same (apart from the weight α_I^S) because we do not have household level data on these

sectors; and 3) $\prod_{m\in M}\left(\frac{s^c_{mIt}}{s^c_{mIt-1}}\right)^{\frac{\alpha_I^{ND} w_{mI}}{\sigma_m - 1}}$ captures the role that new goods play for each income group, or the new-goods bias by income group. For future reference we define $\pi_I = \pi_{ND,I}^{\alpha_I^{ND}} \times \pi_D^{\alpha_I^D} \times \pi_S^{\alpha_I^S}$ as the common goods' price inflation of income group I.

The geometric average of $s^c_{mI,t} / s^c_{mI,t-1}$ ratios captures the difference (or bias) between a true cost-of-living index relative to the common-good price indexes like the CPI. Mechanically, when the share of new UPCs consumed by group *I* in period *t* is larger than the share of UPCs that have disappeared from group *I*'s basket in period *t* –1, this $s^c_{mI,t}$ ratio is smaller than 1. The smaller is this share ratio, the smaller is the overall inflation rate that takes product turnover into account relative to a conventional (common-goods) price index that does not.

The inflation rate in (10) also depends on the good-specific elasticity of substitution, σ_m. As σ_m grows, the term $\frac{1}{\sigma_m - 1}$ approaches zero, and the bias term $\prod_{m\in M}\left(\frac{s^c_{mIt}}{s^c_{mIt-1}}\right)^{\frac{\alpha_I^{ND} w_{mI}}{\sigma_m - 1}}$ becomes unity. That is, when existing varieties are close substitutes to new or disappearing varieties changes in variety will not have a large effect on the difference between π_I and $COLI_I$. By contrast, when σ_m is small, varieties are not close substitutes, $\frac{1}{\sigma_m - 1}$ is high, and therefore new varieties are very valuable and disappearing varieties are very costly. In this case, the conventional price index is not appropriate.

We can now formally see in (10) the three main assumptions that we relaxed relative to standard official measures of inflation. The first difference with a standard representative agent setup is that the inflation of common non-durable goods over time, π_{mI}, has weights that depend on the income-group *I*. Second, the inflation on the set of common goods over time is defined over a set of goods, U_I, that can vary by income group (see equation (9)). Finally, the second term in (8) allows for new and disappearing products to impact income groups differently.

IV. Main Results

In this section we estimate how large are the inflation differentials across households of different income groups, the impact that this had on inequality in the U.S. and we assess the role played in this process by Chinese exports.

V.A Non-Durable Inflation Rates by Income Groups, 1994 – 2005

We use the ACNielsen databases to compute non-durable inflation rates by income groups. For the period 1999 – 2005 we can calculate inflation rates by income group, $\pi_{ND,I}^{\alpha_I}$, by examining the purchases of goods by households in each income group. To more clearly highlight the role of each assumption that has been relaxed relative to the representative agent model, we report the common-goods inflation rate, $\pi_{ND,I}$, without the income specific weight in consumption of non-durable goods, α_I.

The semi-dotted line with no markers in Figure 8 shows the non-durable inflation rate by income group computed using (5) and (9). While the richest group in the ACNielsen had a non-durable inflation rate of around 9.5 percent over the 1999 – 2005 period, or 1.5 percent per year, the four poorest groups combined had an non-durable inflation of 6.2 percent, or 1.0 percent per year. The non-durable inflation rate of the poorest income group was 0.5 percentage points smaller than that of the richest group over the 1999 – 2005 period.

To calculate the different non-durable inflation rates between 1994 and 1999 we use the aggregate database. By definition this database does not include household specific purchases but just an average price paid for each UPC in 1994 and 1999. This prevents us from calculating the price indexes by income group using prices that are specific to each income group. However, we can use the information available in the 1999 Disaggregate data to build the basket of goods consumed by the rich, and the basket of goods consumed by the poor. That is, we can compute the following statistic:

(11)
$$\pi_{mI} = \prod_{u \in U_{mI}} \left(\frac{p_{umt}}{p_{umt-1}} \right)^{w_{umIt}}$$

where the only difference relative to (5) is that the prices of a UPC *u* in module *m* are not the specific to income group *I*, p_{umt}, but the average price paid for that UPC by all households. Note, however, that the basket of goods is allowed to vary by income group, i.e. U_{mI}.

Using (11) as opposed to (5) we compute the first term of (8) based on the aggregate data between 1994 and 1999. The dotted line with round markers in Figure 8 shows the non-durable inflation rate by income group between 1994 and 1999. During this period we compute a non-durable inflation rate for the richest group in our sample to be 8.6 percent, or 1.4 percent per year, while the four poorest groups had a non-durable inflation rate of 7.1 percent, or 1.1 percent per year. Over the 1994 – 1999 period, the non-durable inflation rate of the poorest income group was 0.3 percentage points smaller than that of the richest group.

The solid line combines both facts into a single non-durable inflation rate between 1994 – 1999 and 1999 – 2005 by income group. The differences are notable. The non-durable inflation rate of the poorest households was 14.2 percent over the entire 11 year period, compared to a non-durable inflation above 18.5 percent for the richest households. This implies yearly differences in non-durable inflation rates between the rich and the poor of 0.4 percentage points.

We turn next to the measurement of the second term of equation (10). For expositional ease we report the bias that arises in "fixed" or common-goods price indexes, $\prod_{m\in M}\left(\frac{s^c_{mIt}}{s^c_{mIt-1}}\right)^{\frac{w_{mI}}{\sigma_m-1}}$, without the income specific weight in consumption of non-durable goods, α_I^{ND}. We use the elasticities of substitution estimated in Broda and Weinstein (2007) to compute the estimate of the bias.[17] The typical elasticity value obtained in that paper is around 7, which implies, in a world with imperfect competition and constant markups, a markup of around 16 percent. Notice that the higher this elasticity, the smaller is the bias between a conventional inflation measure and change in the utility based cost-of-living. As mentioned above, we do not allow elasticities to vary by income group. However, as suggested by Figure 6, the number of new UPCs purchased by the poor is larger than those purchased by the rich. On average we see the poor increasing the number of new UPCs purchased by around 10 percent relative to the rich.

[17] The elasticities estimated in Broda and Weinstein (2007) are at the "product group" level. Each product group is comprised of an average of 7 different modules.

One aspect of the data that we need to control is that the share of households in each income group has changed between 1999 and 2005. For instance, households with income below $15,000 were 4.8 percent of the sample in 1999 and 6.5 percent of the sample in 2005. To prevent this change in the number of households from affecting the number of goods being purchased by each income group we calculate the bias keeping the share of households fixed at their 1999 value when using the 2005 sample.

The higher proportion of new goods purchased by the poor has a stark implication for price measurement. Figure 9 shows the average annual bias (second term of equation (10)) by income group. Since we can only perform this calculation using the disaggregate data, the sample period is restricted to 1999 – 2005. During this time, we see that the bias is substantially larger for the poorest households compared to the richest households. The bias is as large as 1 percent per year for the poorest households and 0.6 percent per year for the richest. This effect comes primarily from the fact that the poor purchased more new goods than the rich. This is an effect that is not captured in official statistics and adds an additional wedge between the changes in the true cost-of-living of the poor relative to the rich.

In Figure 10 we show the wedge that the bias drives between common and adjusted inflation rates across income groups. The semi-dotted line with no markers in Figure 10 is identical to that in Figure 8 and shows the inflation rate for non-durable modules by income group. The dotted line with round markers shows the bias-adjusted inflation rate over the 1999 – 2005 period. The differences are even starker across income groups when we look at the bias-adjusted inflation. The figure suggests that the gap between poor and rich inflation rates rises from 0.5 percentage points per year to 1.1 percentage points per year, or almost 7 percent over the 1999 – 2005 period. We will examine the implications that this has for inequality measures in section V.C.

V.B The Role of Chinese Trade

In the previous sub-section we showed that non-durable inflation rates for poor households have been lower than for rich households. In this section we examine how much of this differential impact can be explained by the direct effect of the rise of Chinese exports to the US. As we discuss below, our approach does not capture general equilibrium effects that work

through the skill and unskilled wages in the US. We start our analysis by looking at the impact of China's exports on prices of non-durable goods consumed in America.

The model in the appendix suggests that an expansion of Chinese production possibilities leads to a fall in the price of those goods relative to other goods (i.e., services or sectors in which China cannot export). In principle the expansion of production possibilities of any developing country could have a differential impact on prices of different baskets of goods. However, as we will show below, over the time period studied, most of the empirical effect is coming from the increase in Chinese production possibilities. For this reason we use China in the baseline specifications we provide below, although we present results for a series of developing countries.

Ideally we would like to use Chinese production data by module to proxy for the changes in Chinese production possibilities.[18] Unfortunately these data are not available. For this reason we use $\frac{d(\mathrm{X}_{China-World,mt})}{X_{All-World,mt-1}}$ –i.e., the change in Chinese exports in module *m* to the world as a share of total exports in that module– to proxy for increases in Chinese production possibilities.[19] Moreover, the model suggests that the impact of the Chinese expansion has a differential impact on the basket of households with different income (skill) levels. This motivates the following empirical specification,

$$\ln \pi_{mIt} = \delta + \phi_I \frac{d(\mathrm{X}_{China-World,mt})}{X_{All-World,mt-1}} + \chi Z_{mt} + \varepsilon_{mt} \quad (12)$$

where $\ln \pi_{mI,t}$ is the log change in the common-goods price index of module *m* and group *I* between 1999 and 2003. Finally, Z_{mt} is a number of controls that includes the change in the import share from other regions and the change in tariffs in each module. We also present results using the full cost-of-living index, $COLI_{mI,t}$, as expressed in (8), and allowing for the impact of an increase in Chinese share to differ by the basket of goods of different income groups, i.e. ϕ_I.

The OLS estimates of (12) are potentially biased because of attenuation caused by measurement error and endogeneity. In particular the source of endogeneity that we address

[18] That is, a proxy for θ_m in terms of the model in the appendix.

[19] In appendix B we provide the results for a similar specification based on the change in the export share of Chinese products to the world. Specifically, the alternate regression used is given by the following expression:
$\ln \pi_{mIt} = \delta + \phi_I d(\mathrm{X}_{China-World,mt} / X_{All-World,mt}) + \chi Z_{mt} + \varepsilon_{mt}$

relates to demand shocks. If Chinese production possibilities increased in modules that concurrently had a positive demand shock we may observe [20] We use the share of non-OECD exports (ex – China) to the world in 1994 and the share of Asia's exports (ex-China) to the world in 1994 as instruments for the change in Chinese world export shares between 1999 and 2005.[21,22]

Table 4A reports the estimated coefficients from a more general specification given by $\ln \pi_{mt} = \delta + \phi \frac{d(\mathrm{X}_{e-World,mt})}{X_{All-World,mt-1}} + \chi Z_{mt} + \varepsilon_{mt}$ where the exporter country, *e*, is allowed to vary but the overall price index is not income specific. The first column shows that there is a strong and significant negative relationship between exports from developing countries in particular modules and the common-goods price index in that module. The coefficient $\phi = -0.69$ implies that a 1 percentage point increase in the share of developing countries in a module is associated with a -0.69 percentage point reduction in US prices. Columns 2 and 3 show that the strong negative impact of export increases is coming primarily from the rise in Chinese exports to the world, and not the rest of the developing countries. As we introduce the changes in world exports of other regions, the coefficient on China remains unchanged with no significant change to its standard errors (not included in the table).

Columns (4) to (6) show the impact of Chinese exports on a cost-of-living index adjusted for product turnover and allows us to contrast our approach to that of the BLS. As in the

[20] Since US and European data only match at the 6-digit level, we used this level of aggregation to match with the US retail sales module data.

[21] We are collecting the data necessary to address the measurement error problem. We will instrument the share of Chinese exports in a particular module with the share of Chinese UPCs in each particular module. This information should be independent of the main source of error that arises as modules are matched with the trade data and should be a good instrument. However, this involves scanning thousands of "made in China" products manually. We are in the process to obtain this information.

[22] We also examined whether the role of China is not just picking the expansion of supercenters during this time period. The household level data includes details about shopping channels that can be helpful in distinguishing the rise of Chinese trade from the expansion of supercenters. We repeat a similar exercise as that in Table 4 but allowing for a different impact of Chinese exports on goods sold in different outlet types. In particular, we perform the following regression by outlet type: $\ln\left(\mathrm{p}_{ums2005} / p_{ums1999}\right) = \chi_s + \phi_s d(\mathrm{X}_{China-World,mt}) / X_{All-World,mt-1} + \varepsilon_{ms}$ where $\mathrm{p}_{ums2005}$ is the price of an individual UPC sold in store *s* in 2005. The results suggest that for the complete set of UPCs sold in all stores the β coefficient is negative and significant, which confirms our earlier findings. More interestingly, we observe that the impact on UPC prices of Chinese exports is similar in Traditional Grocery stores and Supercenters like Walmart.

conventional (common-goods) price inflation, Chinese exports help explain the majority of the variation in inflation across modules. It is also interesting to note that the coefficients on the Chinese export variable are always more negative when using the cost-of-living index than when using the conventional common-goods price index. In particular, this suggests that in the sectors where China's export share increased the most, US consumers saw the biggest net increases in new products. This shows up as lower bias-adjusted inflation measures in those sectors. The impact on this measure of inflation is such that a 1 percentage point increase in the Chinese export share in a module is associated with a reduction of 0.80 percentage point in bias-adjusted inflation in that sector.

We examine next whether the impact of Chinese exports more heavily affect the basket of goods consumed by the poor relative to the rich. For this purpose we divide the sample of non-durable goods according to the consumption basket of the lowest decile of the income distribution (which we henceforth call "poor") and the upper decile (which we henceforth call "rich"). We then recomputed common and bias-adjusted inflation measures based on (8). The upper and middle panels show the results of using the same regression specification in (12) on the price indexes based on the basket of goods consumed by the poor and rich, respectively. The results suggest a strong differential impact of China's trade on the prices that each of these income groups face. The poor's sensitivity of non-durable prices to Chinese exports is between 15 to 35 percent larger than the sensitivity of the rich. A 1 percentage point increase in the export share of China in a module is associated with a decline in the prices paid by the poor of between 0.76 and 1.01 percentage points. For the rich, the impact of China's expansion is still negative but more muted. A 1 percentage point increase in the share of China in a module is associated with a decline in the prices paid by the rich of between 0.63 and 0.87 percentage points. For both sets of goods (i.e., panels), the rise in Chinese trade has an impact on the prices of existing goods and on the availability of new products.

A simple way to understand the magnitude of these elasticities is by considering the change in world imports from China in this period (we provide a more thorough counterfactual below). During the 1999 – 2003 the share of Chinese exports to the world increased on average increased by 4 percentage points. This implies that the change in Chinese export shares has reduced non-durable price inflation in the US by 2.75 percentage points over the sample period,

or 0.7 percentage points per year. Since non-durable inflation was 3.1 percent per year over this period, this corresponds to a reduction of non-durable inflation of around 20 percent of the actual inflation level.[23] Moreover, as non-durable consumption constitutes 40 percent of the consumption basket of the poor, the effect of China will have a large impact on the overall CPI of the poor.

V.C Implications for Inequality

Our exploration of the data yielded several important stylized facts that will help us understand the problems in using conventional price indexes in the measurement of inequality. First, inflation differentials across income groups have been large for non-durable goods for the 1994 – 2003 period. Second, the shares of non-durable consumption differ markedly across income groups. Third, Chinese exports are highly concentrated in low quality goods that are disproportionately consumed by the poor. And finally, in sectors where Chinese exports have increased the most, the decline in US non-durable goods' prices have been the largest. We can now put together all of our results and assess the implications that these facts have on the measurement of inequality and the contribution of Chinese exports. We start with the in-sample implications of our results of previous sections. We also examine the out-of-sample implications by using a number of simple assumptions that we explain below.

The differences between conventional inequality measures and the measures of inequality we examine in this paper can be expressed in a simple way. While the conventional inequality measures use a conventional price index that is identical across income groups, we allow for inflation to vary by income group and we capture the possibility that new goods impact inflation in a different way across income groups. This difference can be expressed as follows:

$$(13) \qquad \underbrace{d\ln\left(\frac{w_{90th}}{P}/\frac{w_{10th}}{P}\right)}_{\text{Change in Conventional Inequality Measure}} - \underbrace{d\ln\left(\frac{w_{90th}}{P_{90th}}/\frac{w_{10th}}{P_{10th}}\right)}_{\text{Change in Corrected Inequality Measure}} = d\ln P_{90th} - d\ln P_{10th} = \ln COLI_{90th} - \ln COLI_{10th}$$

[23] We used the "Non-durable" component of the CPI for this calculation which over this period was 3.1 percent per year.

That is, if the rich's inflation rate is higher than that of the poor, then the conventional inequality measure overstates true inequality. We therefore focus next on quantifying the inflation differentials across income groups based on the facts uncovered in previous sections.

In Figures 7, 9 and 10 we have documented that the assumptions underlying the representative agent model where expenditure shares and non-durable inflation rates across income groups are equal are strongly violated in the data. We can directly compute the difference in inflation rates by income group from equation (10). As an intermediate step we summarize some key inputs into this calculation in Table 6. This table shows inflation rates in different sectors of the economy. It highlights that service inflation (excluding housing) has been substantially larger than inflation in non-durable goods. It also describes the findings in Figure 8, where non-durable goods' inflation is found to be lower for the basket of the poor than the basket of the rich.

Using equation (10), the price index series in Table 6, and the expenditure shares by income group (top panel of Table 7A) we can compute inflation differentials by income group. To provide insight into how relaxing three different standard assumptions affect the results, we present the result in three different columns in Table 7B. Column (2) shows the inflation differential between rich and poor by simply allowing for different consumption expenditure weights. We find that the poor's common-goods inflation rate over the 1994 – 2005 period has been 2.1 percentage points smaller than that of the rich. This implies that real income inequality has risen by 2.1 percentage points less than implied by official statistics simply because the conventional CPI measures do not take into account the differences in expenditure shares by consumption category across groups. This effect is mostly coming from the fact that the poor consume more non-durable goods and less services outside of housing, whose prices has risen substantially more than other goods in the economy.[24]

[24] If expenditure shares on durable goods were constant across income groups, then the difference in cost-of-living indexes would reduce to the following expression: $\ln COLI_{90th} - \ln COLI_{10th} = \left(\alpha_{10th}^{ND} - \alpha_{90th}^{ND}\right)\left(\pi_S - \pi_{ND}\right)$. In this case, since both terms are positive in the data, then inflation in the highest decile would be higher than that for the lowest decile - the rich consume a higher share of services, whose price has risen more than that of non-durable goods. In particular, Figure 7B suggests a difference of 10 percentage points in the share that non-durable goods take in the consumption basket of rich versus poor, and Figure 11 shows that service inflation has been around 10 percentage points larger than non-durable inflation over the 1994 – 2005 period. This would suggest an inflation differential over this period of around 1 percentage point.

Column (3) in Table 7B shows the additional effect of allowing for different non-durable "common goods" inflation rates across income groups. By using the income specific common-goods inflation rates, the inflation differential across income groups grows to 3.7 percent. When one takes into account the fact that the proportion of new goods purchased by the poor is larger than for the rich (column (4)), the inflation differentials between rich and poor over the 1994 – 2005 period rise to 5.5 percent. This suggests that corrected measures of inequality imply almost no change in inequality over this period, or a reduction in inequality of around 5.5 percent relative to conventional inequality measures.

We are left next to discuss the role of China in explaining the results of Table 7B. Figure 1 shows the dramatic increase in the share of Chinese goods since 1994, moving from 6 to 17 percent of all US imports. We use the semi-elasticities obtained in Table 4 to calculate the portion of the inflation differences across income groups that can be accounted for by China. Specifically, we use the semi-elasticities found in the IV regressions and the actual change in Chinese exports by module to calculate the direct impact of the rise of China on the overall non-durable price index and on inflation faced by each income groups. When we compute the impact on each income group we allow for weights in each module and ϕ to vary by income group. We comment below on how this exercise ignores general equilibrium effects that work through differences in wages between skilled and unskilled workers.

The three columns in Table 8 show the incremental effect that China has on the difference between conventional and correct inequality measures (i.e., cost-of-living differential across rich and poor). The first column calculates the impact that China has had on the $90^{th}/10^{th}$ ratio that allows for the weights on consumption of non-durables and services to vary across income groups. The impact that Chinese exports have on the inflation of non-durable goods reduces the $90^{th}/10^{th}$ ratio by 1.3 percent. Relaxing the assumption that the basket consumed by the poor is the same as that of the rich (column 2) implies almost an additional 1.5 percentage point lower inequality ratio. The reasons for this additional effect is that China has reduced the price of the poor's basket relatively more than that of the rich (see coefficients on columns (2) and (5) of Table 5). Finally, the last column shows that since the impact of China has been larger on bias-adjusted inflation measures and larger for the poor than the rich (columns 4-7 in Table 5) inequality measures corrected for these effects add another 0.1 percentage points to the reduction

in the poor's relative prices. Overall, we find that Chinese exports alone can help offset around 30 percent of the rise in conventionally measured inequality documented since 1994 (last column).

While the exercise in Table 8 provides a unique link between trade data and domestic prices and quantities of goods sold in US retail stores, the restriction of the data being only on non-durable goods implies that we are ignoring two important general equilibrium effects of the of the Chinese trade on US prices. First, in the model in the appendix we show that an expansion in the set of goods that China can produce has general equilibrium effects on the prices of services (non-traded goods). As services are more skilled intensive, an expansion of trade with China rises the wages of the skilled relative to the unskilled in the US. This might tend to increase the price of services in the US relative to less skill intensive sectors. If part of the rise in the price of services is due to China, this implies that we are understating the role that China has on the gap in inflation differentials across income groups. Second, even within non-durable goods, Chinese exports might not be expanding in skill-intensive sectors whose prices are rising faster than without the expansion of China. If these goods are more heavily consumed by the rich, this would tend to increase the role of China in explaining the inflation differentials.

V. Conclusion

The debate on trade and wages in the U.S. has entirely focused on the impact that trade with developing countries has on the wages of the unskilled in America. This debate has overlooked the impact that trade has on prices of the goods consumed by different income groups. In particular, since developing countries typically produce low quality goods that are disproportionately consumed by the poor in America, this implies that inequality measures that do not correct for differences in the basket of goods consumed by rich and poor neglect this "price" effect of trade.

Using detailed household consumption data between 1994 and 2005, we find that this "price effect" offsets almost all the rise in inequality measured by official statistics over this period. In particular, this offsetting effect comes from the fact that non-durable inflation faced by the poor was smaller than that of the rich, the poor consume a larger share of non-durable goods –whose

inflation has been smaller than for services–, and the introduction of new goods have disproportionately benefitted the poor over this period. Moreover, by matching detailed US trade data with consumption patterns of households of different income groups in the US, we argue that the rise of Chinese trade has helped reduce the relative price index of the poor by around 0.3 percentage points per year. This effect alone can offset around a third of the rise in official inequality we have seen over this period.

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Table 1A: ACNielsen "Non-Durable" Homescan Database 1994, 1999 - 2003

Year	1994	1998	1999	2000	2001	2002	2003	2004	2005
# Households	n.a.	41,500	41,500	55,000	55,000	55,000	55,000	n.a.	n.a.
# UPCs	532789	n.a.	651343	666445	658055	690036	697312	n.a.	n.a.
# Modules	1097	n.a.	1096	1095	1093	1092	1093	n.a.	n.a.

Table 1B: ACNielsen "Food" Homescan Database 1998 - 2005

Dairy Products

	1994	1998	1999	2000	2001	2002	2003	2004	2005
# Households	n.a.	7623	7123	7520	8208	8673	8817	39473	38746
# UPC Codes	n.a.	26617	26364	26540	26631	26925	26896	37236	37365
# Modules	n.a.	43	43	43	43	43	45	45	45

Dry Grocery Products

	1994	1998	1999	2000	2001	2002	2003	2004	2005
# Households	n.a.	n.a.	7124	7523	8215	8683	8832	39572	38856
# UPC Codes	n.a.	n.a.	159099	160502	163847	167823	169318	253332	256084
# Modules	n.a.	n.a.	417	417	418	417	417	417	417

FPM Products

	1994	1998	1999	2000	2001	2002	2003	2004	2005
# Households	n.a.	7624	7123	7520	8210	8672	8822	n.a.	38793
# UPC Codes	n.a.	44602	44216	44562	46037	47351	47996	n.a.	73377
# Modules	n.a.	133	133	133	133	135	134	n.a.	135

Random Weight Products

	1994	1998	1999	2000	2001	2002	2003	2004	2005
# Households	n.a.	7623	7119	7496	8128	8568	8694	8355	8034
# UPC Codes	n.a.	5248	7623	12952	12360	15836	15592	15269	15118
# Modules	n.a.	22	43	43	43	41	43	43	43

All Products

	1994	1998	1999	2000	2001	2002	2003	2004	2005
Total # UPC codes	n.a.	76467	237302	244556	248875	257935	259802	305837	381944
Total # Modules	n.a.	198	636	636	637	636	639	505	640

Table 2: Descriptive Statistics US Import Data 1972 - 2005

	7-digit TSUSA data		10-digit HTS data	
	1972	1988	1991	2005
TOTAL EXPORTS TO THE US				
Number of TSUSA/HTS	7731	12822	17142	16862
Number of Countries	210	210	228	228
Number of Shipments per Country	7731	12822	14341	25593
Number of Shipments per Country per HTS	1	1	0.84	1.52
CHINESE EXPORTS TO THE US				
Number of TSUSA/HTS	730	5676	8741	12716
Share of Total	0.09	0.44	0.51	0.75
Number of Shipments per Country	730	5676	215959	979753
Number of Shipments per Country per HTS	1	1	24.71	77.05

Table 3

Concordance HTS Categories and ACNielsen's Modules

Module	Module Description	HTS	HTS Description
1046	FRUIT PUNCH BASES & SYRUPS	2106904600	SYRUPS DERIVED FROM CANE OR BEET SUGAR, CONTAINING ADD
1109	TOMATO SAUCE	2103204020	TOMATO SAUCES, NESOI, IN CONTAINERS HOLDING LESS THAN 1
1186	MUSTARD	2103304000	MUSTARD, PREPARED
1290	SOUP-CANNED	2104100040	SOUPS, BROTHS AND PREPARATIONS THEREOF, BASED ON FISH C
1316	PEAS & LENTILS & CORN - DRY	713101000	PEAS (PISUM SATIVUM), SEEDS OF A KIND USED FOR SOWING, DF
1463	GROUND AND WHOLE BEAN COFFEE	901110010	COFFEE, ARABICA, NOT ROASTED, NOT DECAFFEINATED
1469	BAKING POWDER	2102300000	BAKING POWDERS, PREPARED
1490	COUGH DROPS	2106903900	ARTIFICALLY SWEETENED COUGH DROPS
2664	FROZEN FRUITS	811100020	STRAWBERRIES, UNCOOKED OR COOKED BY STEAMING OR BOILI
2672	ICE CREAM - BULK	2105002000	ICE CREAM, WHETHER OR NOT CONTAINING COCOA, NESOI
3593	YEAST-REFRIGERATED	2102100000	YEASTS, ACTIVE
3608	MARGARINE AND SPREADS	2106903800	BUTTER SUBSTITUTES, WHETHER IN LIQUID OR SOLID STATE, CON
6009	HAIR CARE AND FASHION ACCESSOR	9603294010	HAIRBRUSHES,VALUED NOT OVER .40 EACH
6817	FRUIT JUICE - ORANGE	2106904800	ORANGE JUICE, FORTIFIED WITH VITAMINS OR MINERALS
7182	INSECTICIDE - ANT -TRAPS	3808102500	INSECTICIDES CONTAINING ANY AROMATIC OR MODIFIED AROM.
7410	CAMERAS	9006521020	CAMERAS FOR ROLL FILM OF A WIDTH LESS THAN 35MM, FIXED F
7421	FILM	3702510000	FILM FOR COLOR PHOTOGRAPHY (POLYCHROME) OF A WIDTH NO
7464	TOBACCO-SMOKING	2401208390	TOBACCO NESOI, THRESHED OR SIMILARLY PROCESSED, PARTLY O
7780	BODY MASSAGER APPLIANCE AND AC	9019102020	MASSAGE APP,ELEC,BATRY,HANDHLD
7785	COOKWARE PRODUCT	7323915020	BAKWRE OF CAST IRON, NOT ENAMELED
7785	COOKWARE PRODUCT	7323940020	COOKING WARE, ENAMELED STEEL, OTHER THAN STAINLESS, ANI
8401	VITAMINS-B COMPLEX W/C	3004501000	VITAMIN B2
8403	TOOTHBRUSHES	9603210000	TOOTHBRUSHES
8465	COLOGNE & PERFUME-WOMEN'S	3303003000	PERFUMES AND TOILET WATERS CONTAINING ALCOHOL
8530	FIRST AID - THERMOMETERS	9025114000	THERMOMETERS LIQUID-FILLED, FOR DIRECT READING, EXCEPT C

Table 4

The Impact of Changes in Chinese Share on Prices of Non-Durable Goods, 1999 - 2003

	Overall Basket					
Dependant Variable	ln (π_m)	ln (π_m)	ln (π_m)	ln ($COLI_m$)	ln ($COLI_m$)	ln ($COLI_m$)
Method of Estimation	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{d(X_{China-World,mt})}{X_{All-World,mt-1}}$	-0.689		-0.733	-0.796		-0.848
	[0.070]**		[0.072]**	[0.081]**		[0.083]**
$\frac{d(X_{DevelopingexCHN-World,mt})}{X_{All-World,mt-1}}$		-0.109	0.072		-0.127	0.083
		[0.043]*	[0.046]		[0.049]*	[0.052]
Constant	0.051	0.028	0.041	0.037	0.011	0.026
	[0.005]**	[0.008]**	[0.008]**	[0.006]**	[0.009]	[0.009]**
Observations	604	604	604	605	605	605

Robust standard errors in brackets; * significant at 5%; ** significant at 1%

Table 5

The Impact of Changes in Chinese Share on Prices of Non-Durable Goods By Income Group, 1999 - 2003

	Poor's Basket				Rich's Basket			
	ln (π_m)	ln (π_m)	ln ($COLI_m$)	ln ($COLI_m$)	ln (π_m)	ln (π_m)	ln ($COLI_m$)	ln ($COLI_m$)
	(1)	(2)	(3)	(4)	(4)	(5)	(6)	(7)
$\frac{d(X_{China-World,mt})}{X_{All-World,mt-1}}$	-0.762	-0.856	-1.006	-1.011	-0.632	-0.635	-0.873	-0.812
	(5.24)**	[0.168]**	[0.207]**	[0.220]**	[0.111]**	[0.128]**	[0.158]**	[0.172]**
$\frac{d(X_{DevelopingexCHN-World,mt})}{X_{All-World,mt-1}}$		0.084		0.266		0.003		0.133
		[0.081]		[0.130]*		[0.063]		[0.105]
Constant	0.056	0.049	-0.005	-0.029	0.05	0.049	-0.027	-0.039
	(7.02)**	[0.010]**	[0.012]	[0.016]	[0.006]**	[0.008]**	[0.010]**	[0.013]**
Observations	499	499	533	533	542	542	559	559

Robust standard errors in brackets; * significant at 5%; ** significant at 1%

Table 6

Disaggregate Inflation and Inflation by Income Groups, 1984 - 2005

	BLS Price Index					Broda - Romalis Price Index			
	Services less Housing	Housing	Durables less Vehicles	New vehicles	Nondurables	Nondurables Poor	Nondurables Rich	Nondurables Poor w/o Bias	Nondurables Rich w/o Bias
1984	105.1	103.6	107.6	102.6	102.5				
1994	172.4	144.8	112.0	137.6	136.8	136.8	136.8		
1999	201.5	163.9	109.1	142.9	151.2	150.0	152.4	150.0	152.4
2005	247.7	195.7	92.7	137.9	180.2	176.0	184.5	165.0	178.2
	Inflation (in percent)								
2005 - 1984	135.6	88.9	-13.8	34.4	75.8	.	.	.	.
2005 - 1994	43.6	35.2	-17.2	0.2	31.7	28.7	34.9	.	.
2005 - 1999	22.9	19.4	-15.0	-3.5	19.2	17.3	21.1	10.0	16.9

Source: BLS and authors' calculation.

Table 7A

The Impact of Group Specific Inflation on Inequality in the US, 1984 - 2005

	Alternative Assumptions						
Expenditure Shares	CEX All	Poor	Rich	Poor	Rich	Poor	Rich
Prices Used	BLS	BLS	BLS	Broda-Romalis	Broda-Romalis	Broda-Romalis	Broda-Romalis
New Goods / Quality Bias	yes	yes	yes	yes	yes	no	no
	(1)	(2)	(3)	(4)	(5)	(6)	(6)
	CEX Expenditure Shares						
Durable	12.1	11.7	12.5	11.7	12.5	11.7	12.5
Non-Durable	33.6	39.0	28.2	39.0	28.2	39.0	28.2
Services	54.4	49.6	59.2	49.6	59.2	49.6	59.2
Durable (ex - Cars)	5.5	6.1	4.9	6.1	4.9	6.1	4.9
Cars	6.6	5.6	7.7	5.6	7.7	5.6	7.7
Services (ex - Housing)	17.9	8.8	26.9	8.8	26.9	8.8	26.9
Housing	36.5	40.7	32.3	40.7	32.3	40.7	32.3
	Inflation (in percent)						
"In Sample"							
2005 - 1994	31.8	30.4	32.5	29.2	33.3	26.2	32.1
2005 - 1999	17.2	17.1	17.9	16.4	18.4	13.7	17.3
"Out of Sample"							
2005 - 1984	88.0	79.5	87.7	77.9	88.9	73.8	87.1

Source: CBO(2006) and authors' calculation.

Table 7B

The Impact of Group Specific Inflation on Inequality in the US, 1984 - 2005

	Change in Conventional Inequality	Adjustment Due To: Group-Specific Weights	Group-Specific Weights and Baskets	Group-Specific Weights, Baskets, Bias
"In Sample"				
2005 - 1994	5.7	-2.1	-3.7	-5.5
2005 - 1999	7.2	-0.8	-1.7	-3.3
"Out of Sample"				
2005 - 1984	16.9	-8.2	-10.9	-13.4

Table 8

The Impact of Chinese Imports on Inequality in the US (1994 - 2005)

	Group-Specific Weights	Group-Specific Weights and Baskets	Group-Specific Weights, Baskets, Bias
	Change 90/10th Income Ratio Accounted by China (in Percent)		
2005 - 1994*	-1.2	-1.5	-1.6
2005 - 1999	-0.6	-0.8	-0.8
	Share of Inequality Rise *Offset* by China		
2005 - 1994*	21%	27%	28%
2005 - 1999	8%	10%	11%

* Coefficients Based on Regressions in Table 4 and 5.

Figure 1

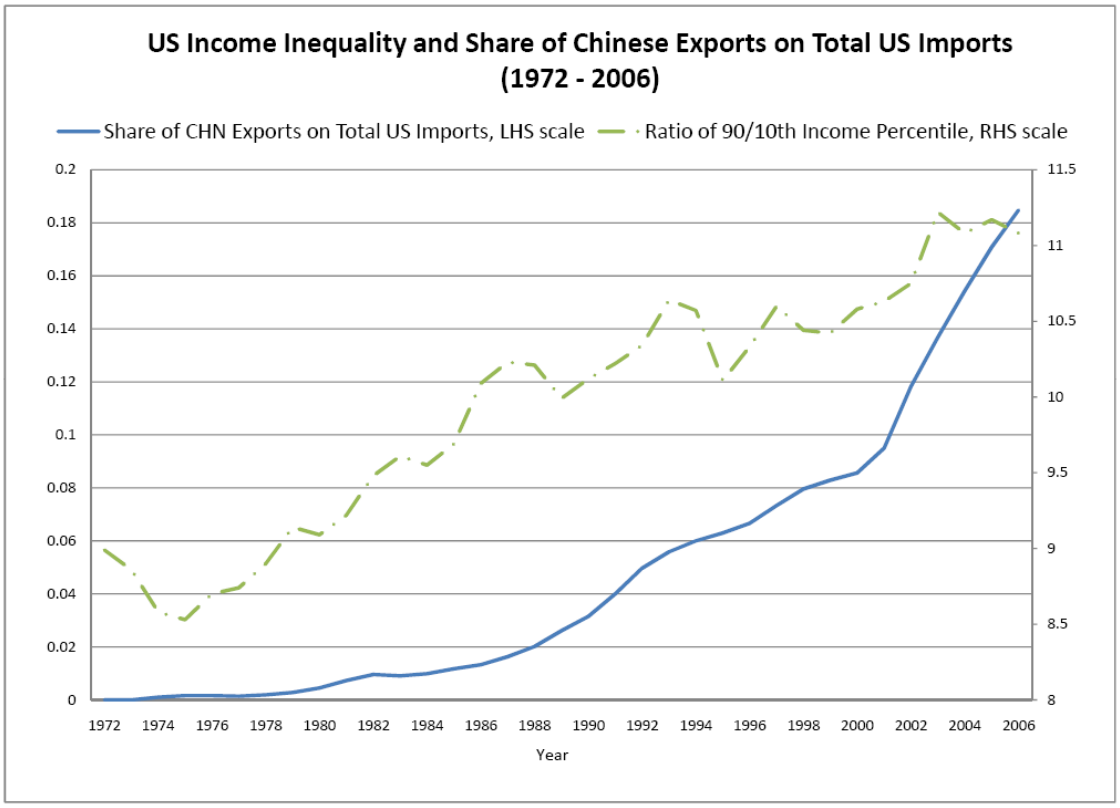

US Income Inequality and Share of Chinese Exports on Total US Imports (1972 - 2006)
Share of CHN Exports on Total US Imports, LHS scale
Ratio of 90/10th Income Percentile, RHS scale
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
11.5
11
10.5
10
9.5
9
8.5
8
1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006
Year

Figure 2A

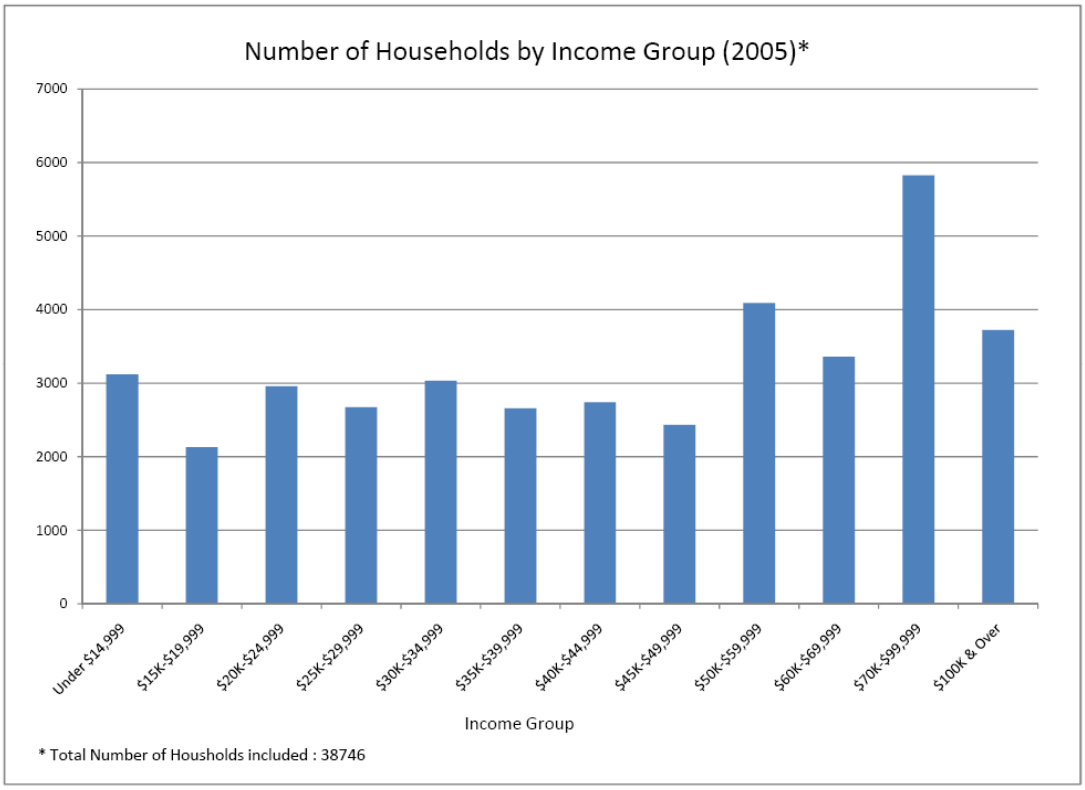


Figure 2B

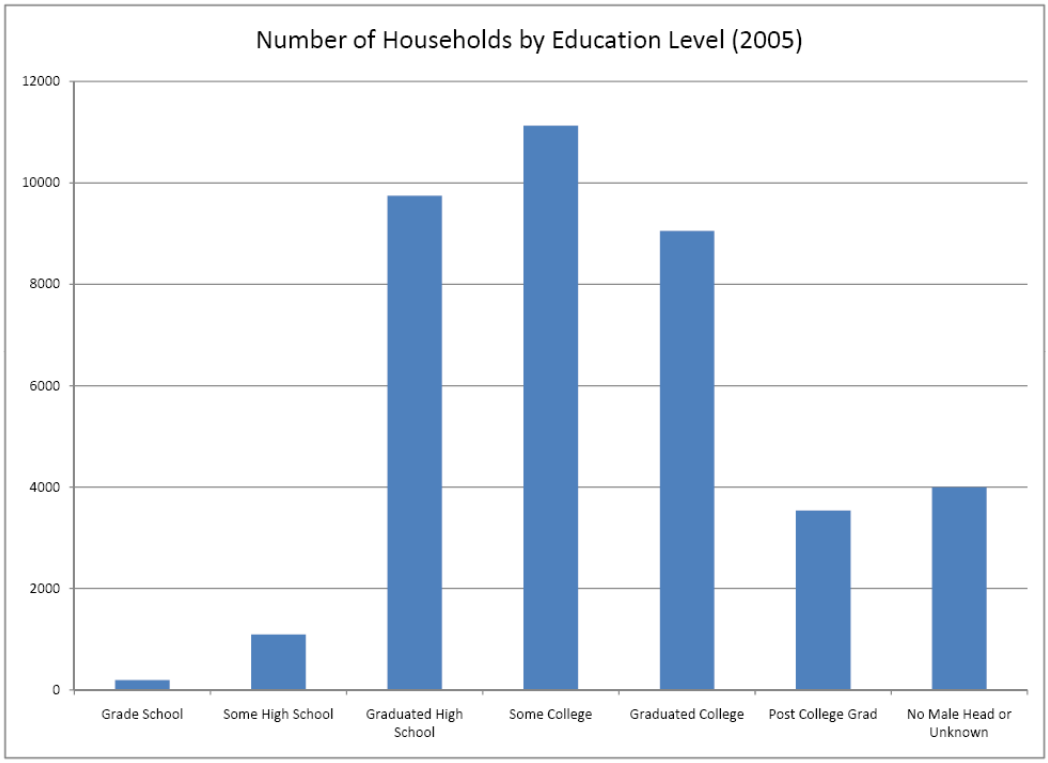


Figure 3A

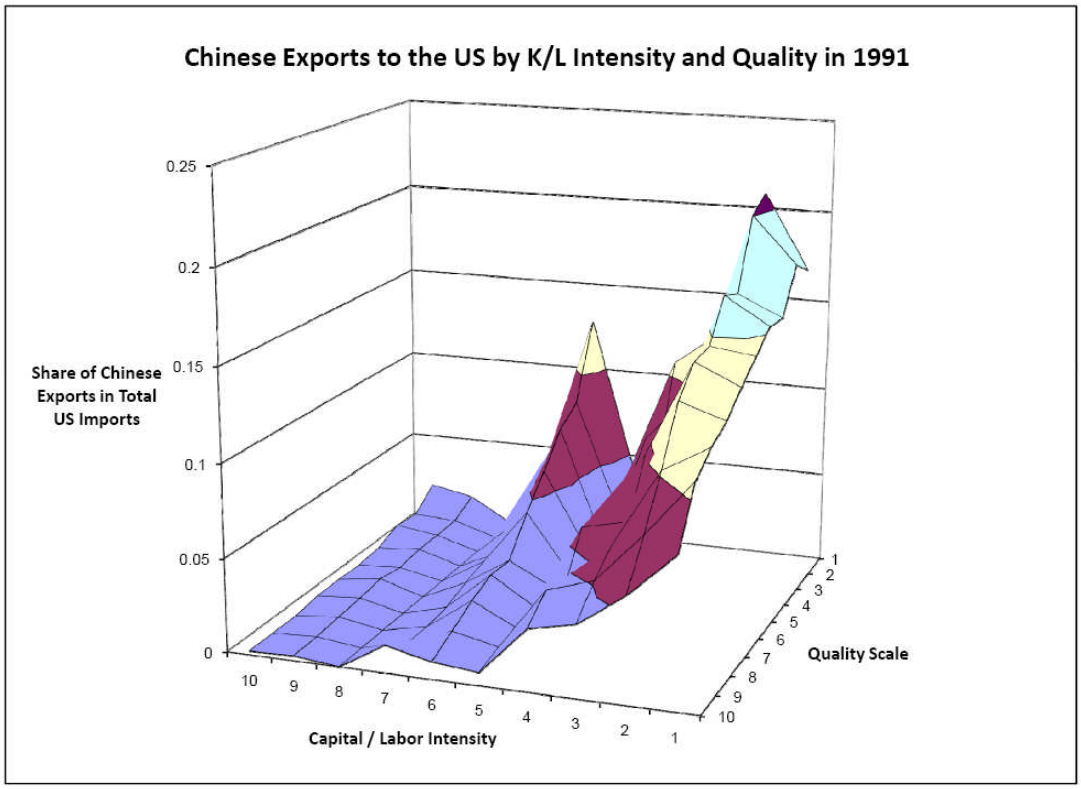


Figure 3B

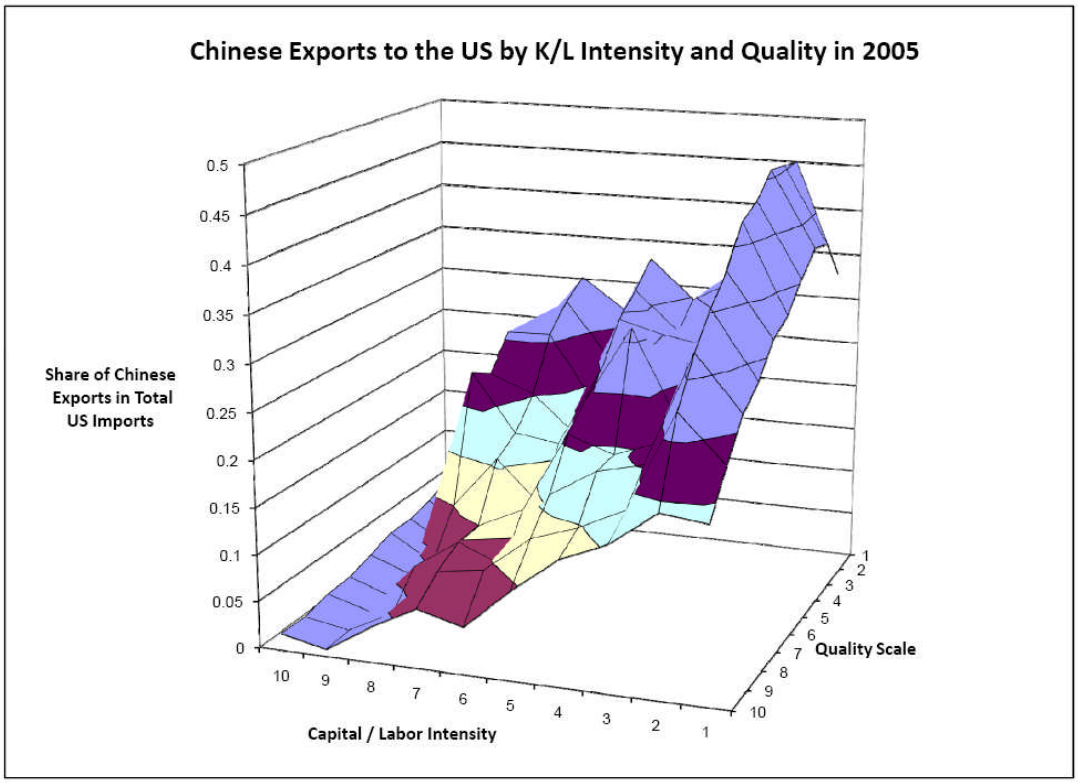


Figure 4A

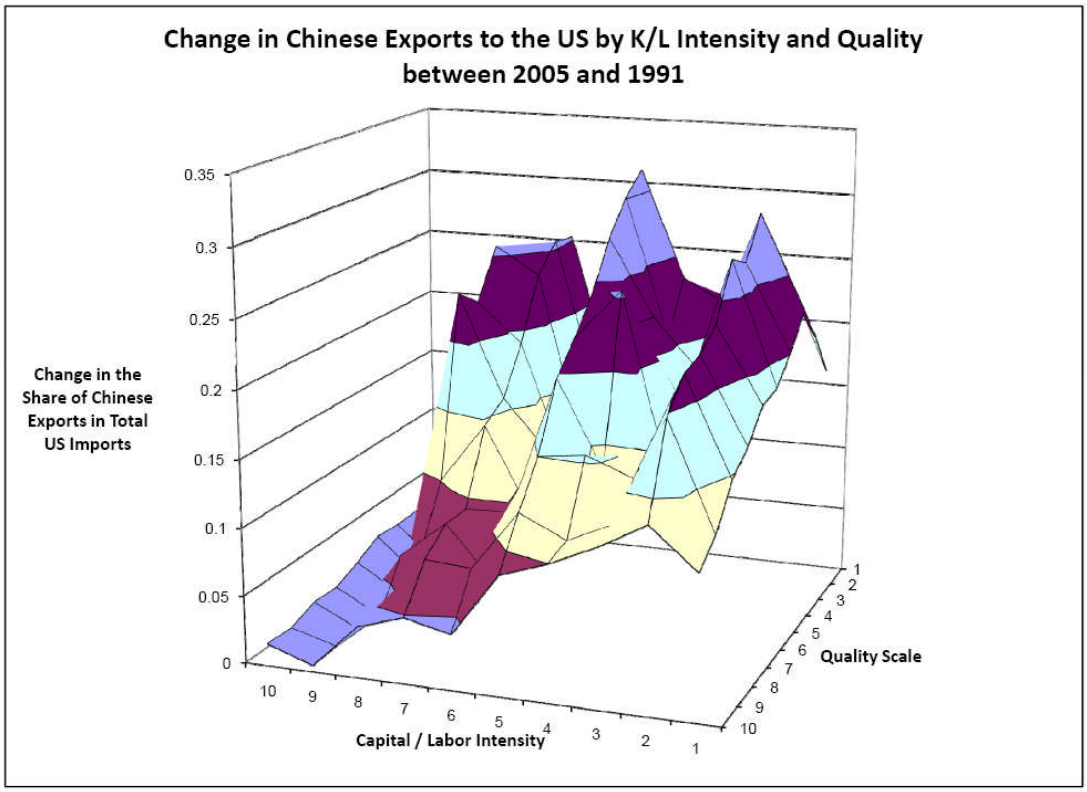


Figure 4B

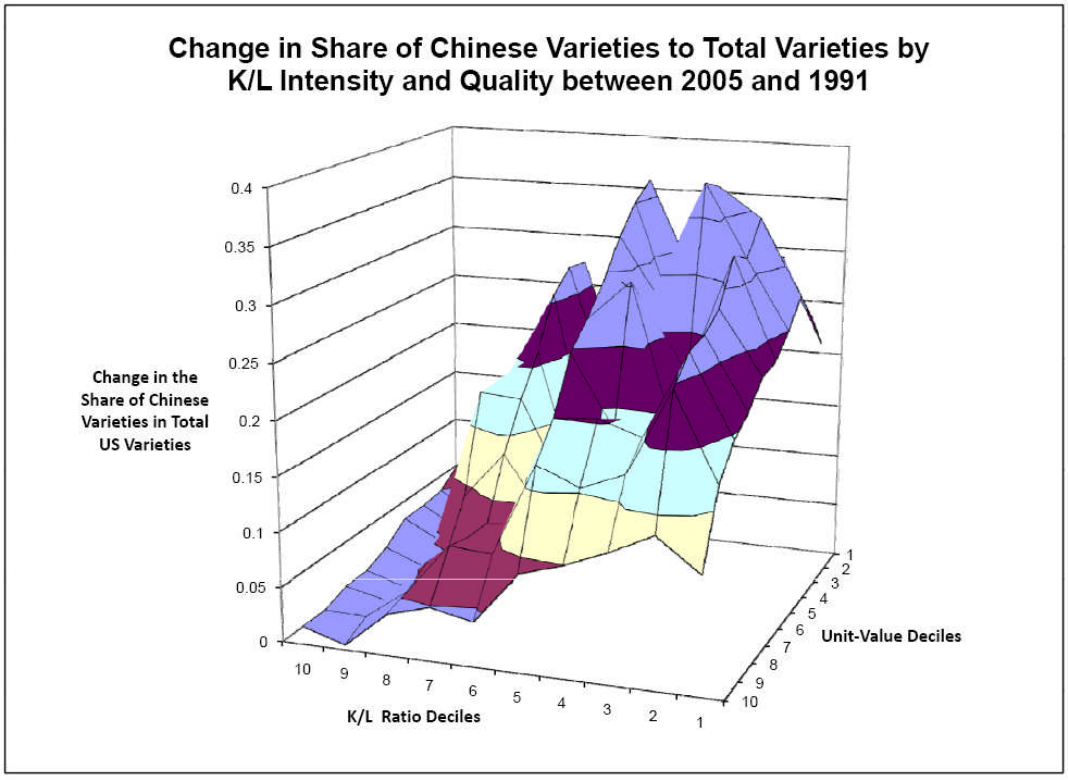


Figure 5

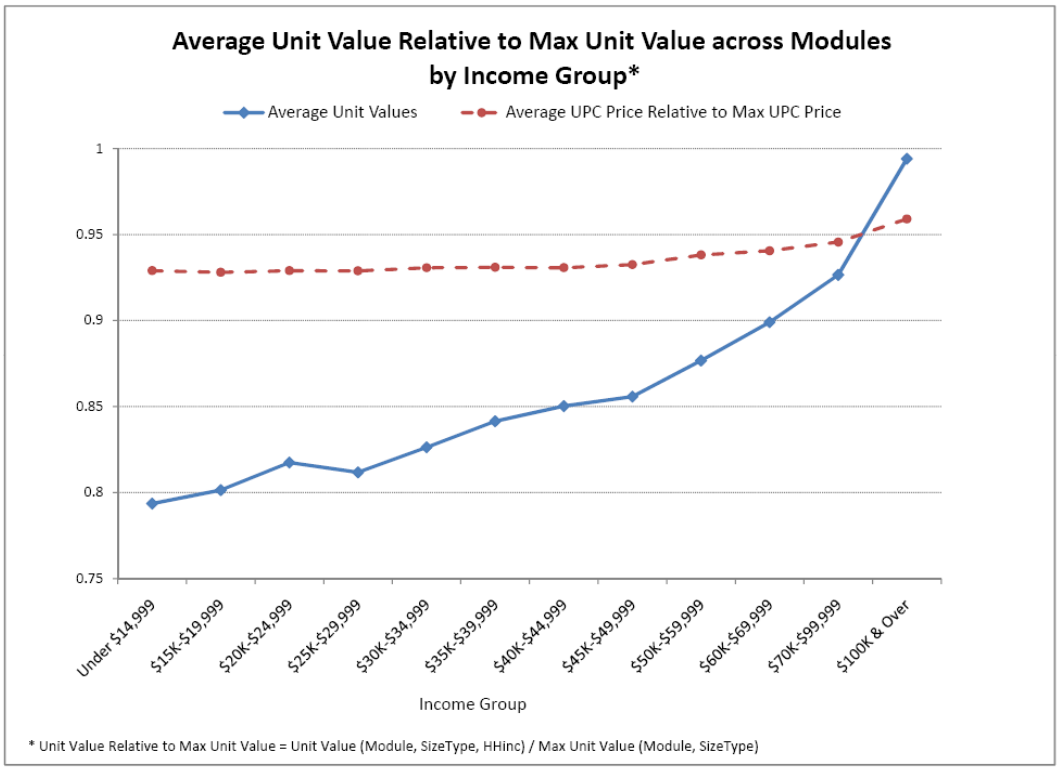


Figure 6

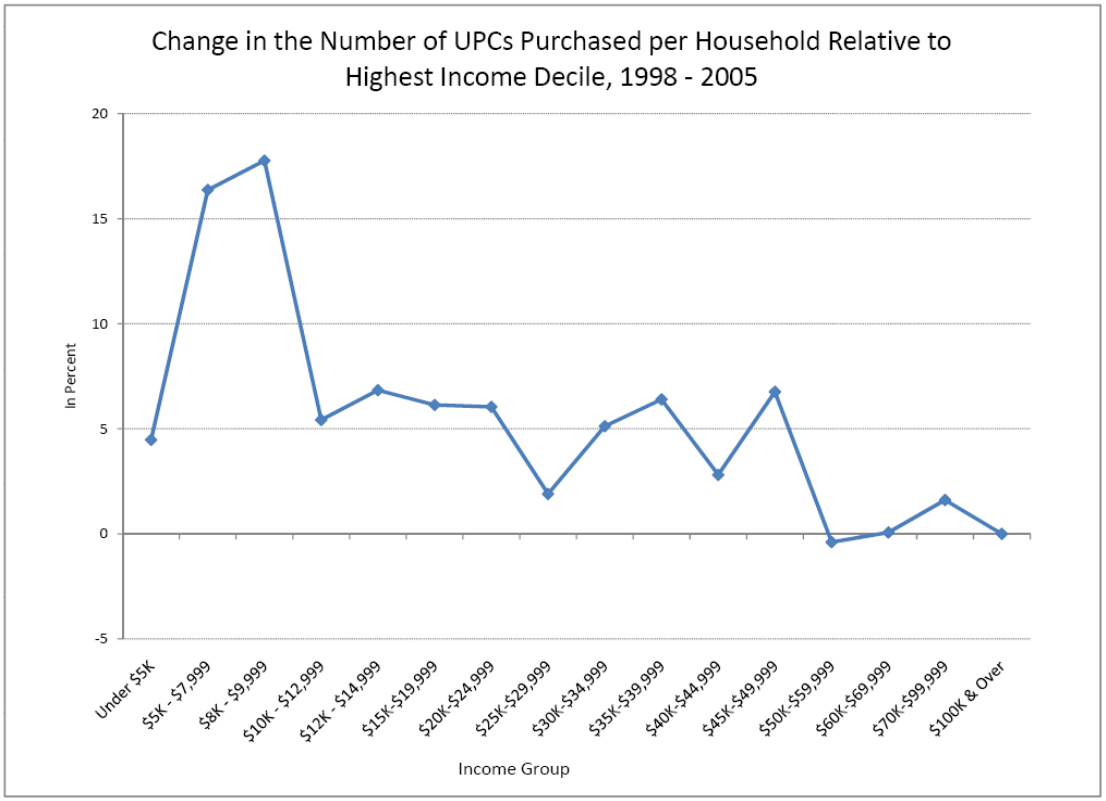


Figure 7A

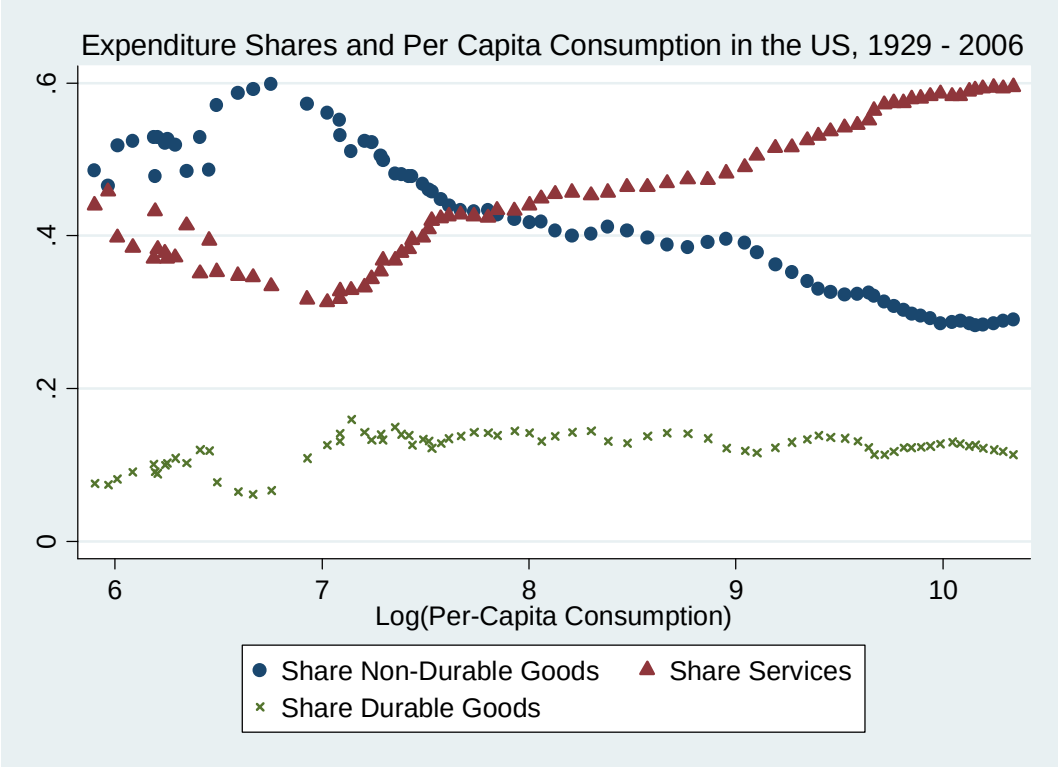


Figure 7B

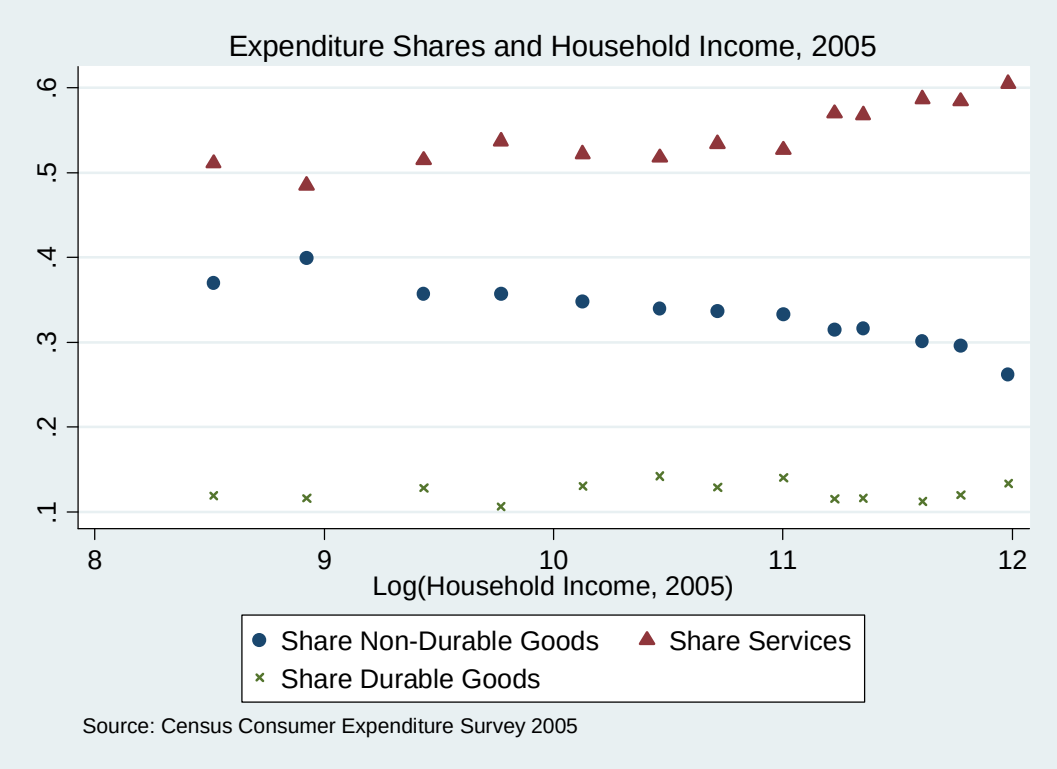


Figure 8

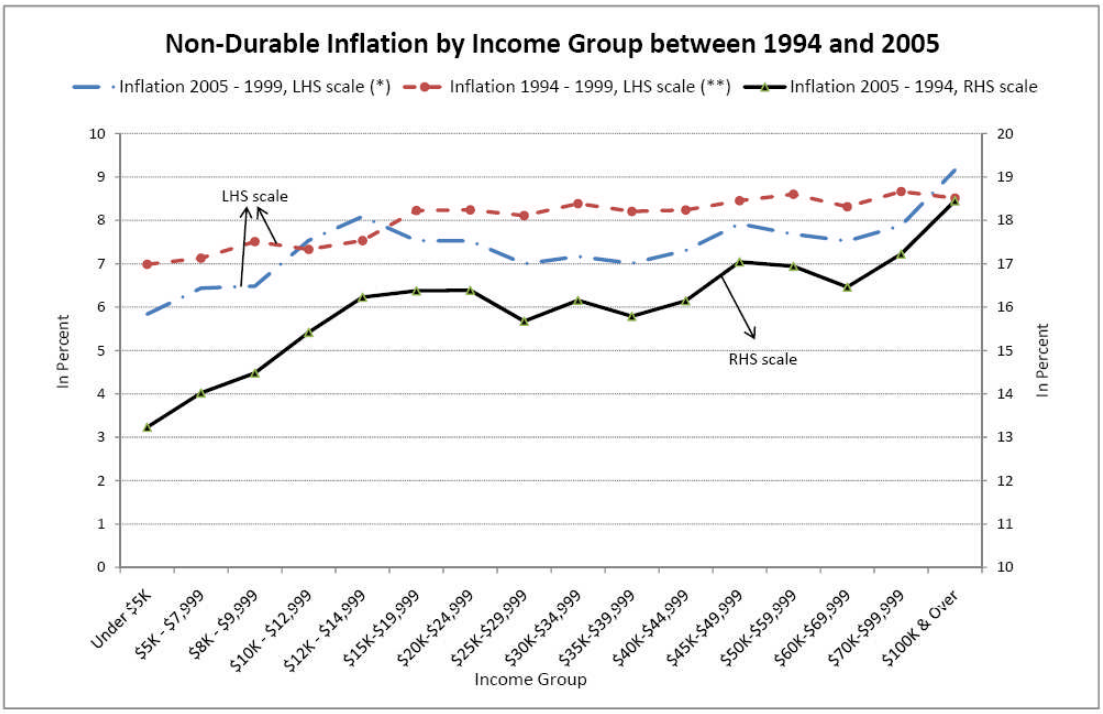


Figure 9

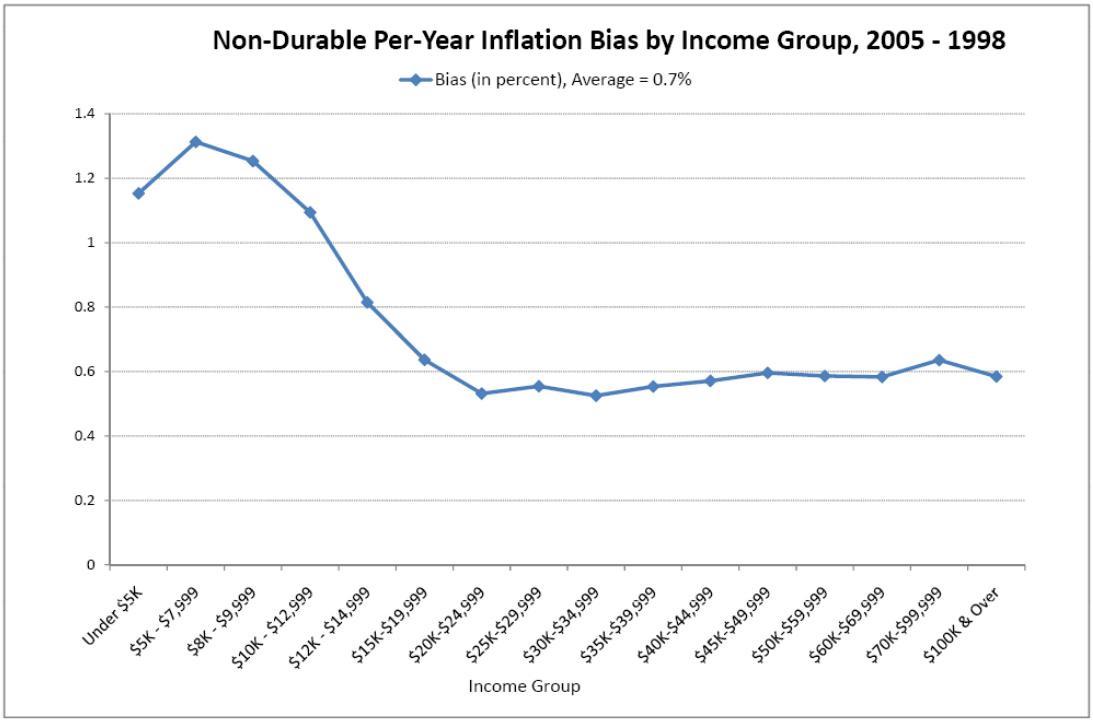
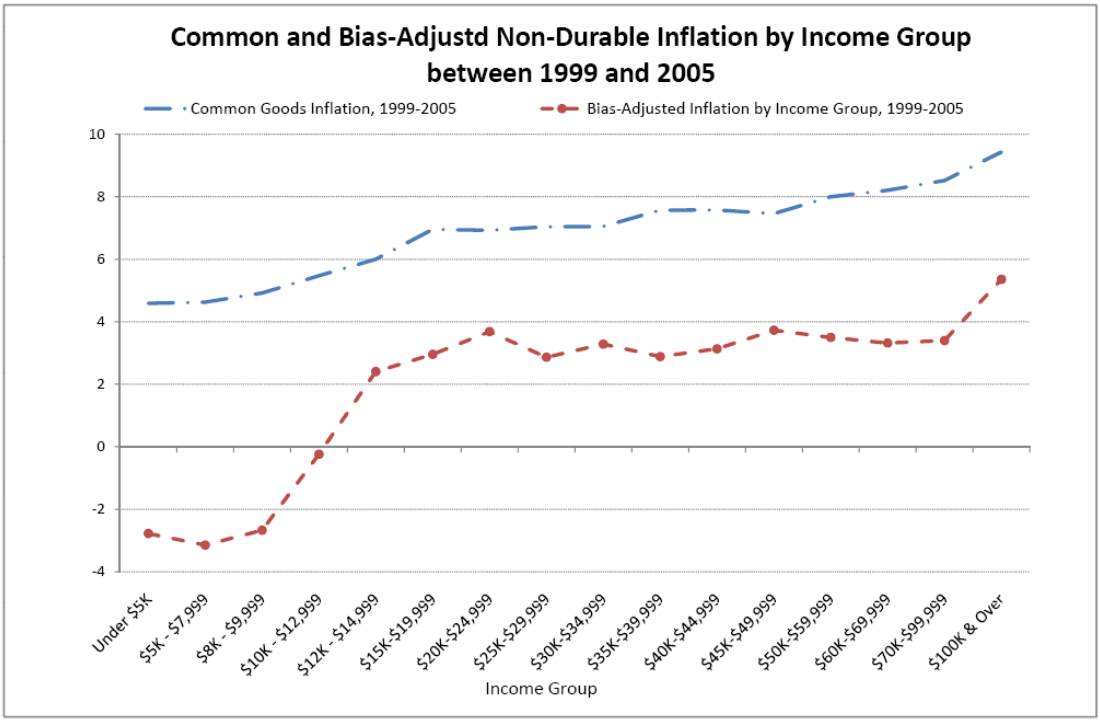

Non-Durable Per-Year Inflation Bias by Income Group, 2005 - 1998
Bias (in percent), Average = 0.7%
1.4
1.2
1
0.8
0.6
0.4
0.2
0
Under $5K
$5K - $7,999
$8K - $9,999
$10K - $12,999
$12K - $14,999
$15K-$19,999
$20K-$24,999
$25K-$29,999
$30K-$34,999
$35K-$39,999
$40K-$44,999
$45K-$49,999
$50K-$59,999
$60K-$69,999
$70K-$99,999
$100K & Over
Income Group

Figure 10


Common and Bias-Adjustd Non-Durable Inflation by Income Group between 1999 and 2005
Common Goods Inflation, 1999-2005
Bias-Adjusted Inflation by Income Group, 1999-2005
10
8
6
4
2
0
-2
-4
Under $5K
$5K - $7,999
$8K - $9,999
$10K - $12,999
$12K - $14,999
$15K-$19,999
$20K-$24,999
$25K-$29,999
$30K-$34,999
$35K-$39,999
$40K-$44,999
$45K-$49,999
$50K-$59,999
$60K-$69,999
$70K-$99,999
$100K & Over
Income Group

Appendix A: Trade Model with Poor and Rich Households

The basic theory underlying the impact of trade on wages is well established. However, existing work does not allow for the impact of lower prices that result from trade to differ across income groups. Therefore, in this section we present a model of trade in which skilled and unskilled workers differ in the set of goods they consume. In particular, unskilled workers – no matter where they reside – consume a higher share of lower quality products. The main purpose of the model is to show that as trade with unskilled abundant countries increases the *real* wage inequality between skilled and unskilled workers does not necessarily deteriorate in the skill-abundant country.

The main setup is an extension of a Ricardian model of trade. Assume that there are 2 countries, the USA and China. Variables for China, where needed, are marked with an asterisk. There are two immobile factors of production, skilled and unskilled labor, that are supplied inelastically. Unskilled labor and skilled labor earn factor rewards w and s respectively. The total labor supply in the US is normalized at 1 and the labor supply in China is 4. For ease in solving the model and without loss of generality, we assume that 50 percent of labor is unskilled in both

countries. Allowing the share of unskilled labor to exceed 50 percent in China would only exacerbate the main result but at the cost of adding complexity to the expressions.

The product space is characterized by a continuum of industries *m* on the interval [0,1]. Each industry contains a continuum of products *z* on the interval [0,1] ranked by quality. The quantity of product *z* in industry *m* is q_{zm}. For expositional ease, we assume that preferences differ across worker types such that unskilled workers exogenously spend more of their income on low-quality goods. Of course, any utility function where low quality goods are inferior would render such result. In particular, all unskilled workers in both countries are assumed to have identical Cobb-Douglas preferences with the fraction of income spent on product *z* in industry *m* being 2-2*z* (equation (3)) All skilled workers in both countries are assumed to have identical Cobb-Douglas preferences with the fraction of income spent on product *z* in industry *m* being 2*z* (equation (15)).

(14) $$\ln U_L = \int_0^1 \int_0^1 (2 - 2z) \ln q_{zm} \, dz \, dm$$

(15) $$\ln U_S = \int_0^1 \int_0^1 2z \ln q_{zm} \, dz \, dm$$

Goods are produced using both factors of production with a constant marginal cost. Production technology in the US, represented by a total cost function *TC*, is assumed to be Cobb-Douglas in both factors:

(16) $$TC(q_{zm}) = q_{zm} s^z w^{1-z}$$

Note that a direct implication of this total cost function is that higher quality goods are more skill-intensive. The Cobb-Douglas nature of the function implies that factor shares do not depend on factor rewards. The index *z* ranks products by quality and by skill intensity, because *z* denotes both the products quality and skilled-labor's share of income in that industry.

We exogenously assume that in each industry *m* China knows how to produce goods only in the quality interval $[0,\theta_m]$. For this range of products, Chinese production technology is identical to that in the US.[25] China is unable to produce any product with quality higher than θ_m.

[25] It would be easy to allow Chinese productivity in these sectors to be some fraction of that in the US – this would effectively reduce Chinese labor supply.

There is free entry into each industry, so in equilibrium profits are zero. Finally, international trade is assumed to be costless.[26]

III.A. Equilibrium

In general equilibrium consumers maximize utility, firms maximize profits, all factors are fully employed and the current account is balanced. Product *z* will only be produced in the lowest cost location. Define $\bar{q} = \int_0^1 q_m dm$. Provided $\bar{q}$ is not too high, in equilibrium China will be the low-cost producer in industry *m* of products [0, θ_m] and the US will produce products (θ_m,1].[27] The US unskilled wage *w* is normalized to 1. It is possible to solve for wages of other factors and the ideal price indexes for unskilled and skilled workers.

Worldwide expenditures on US-produced products get paid to US factors, while worldwide expenditures on Chinese-produced goods get paid to Chinese factors. It is useful to show that the share of the worldwide wage-bill going to skilled labor is invariant to $\bar{q}$. The share of expenditures on product $z \in (\theta_m, 1]$ paid to US skilled labor is *z*, the share going to unskilled labor is *1-z*. The share of expenditures on product $z \in [0, \theta_m]$ paid to Chinese skilled labor is *z*, the share going to unskilled labor is *1-z*. Two times the worldwide skilled wage-bill is given by:

$$\begin{aligned} s + 4s^* &= \int_0^1 \int_0^1 \left[z\left(s + 4s^*\right) + \left(2 - 2z\right)\left(1 + 4w^*\right) \right] z\,dz\,dm \\ &= \frac{2}{3}\left(s + 4s^*\right) + \frac{1}{3}\left(1 + 4w^*\right) \\ &= 1 + 4w^*. \end{aligned}$$

That is, the share of world-wide expenditures on every good is invariant to $\bar{q}$, and in this particular case expenditures on every good are equal. Therefore the skilled wage in the US is given by:

[26] Since we are interested in the implications to the US of increase trade with China, a θ = 0, can be interpreted as a prohibitive transport cost such that the US equilibrium would be the same as in autarky.

[27] The condition is given by the following inequality: $\frac{\bar{\theta}(2-\bar{\theta})}{4(1-\bar{\theta})^2} \leq 1$, which as will be clear below prevents unskilled wages in China to rise above those in the US.

(17) $$\frac{s}{w} = s = \frac{\int_0^1 \int_{q_m}^1 2z\,dz\,dm}{\int_0^1 \int_{q_m}^1 (2-2z)\,dz\,dm} = \frac{1+\bar{q}}{1-\bar{q}}$$

Worldwide expenditures on Chinese-produced products get paid to Chinese factors. The skilled wage in China relative to the unskilled wage is given by:

(18) $$\frac{s^*}{w^*} = \frac{\bar{q}}{2-\bar{q}}$$

We can then use the trade balance condition to solve for Chinese wages relative to the unskilled wage in the US. The following expression equates the US expenditures on Chinese goods and the Chinese expenditures on US products:

(19)

$$s\int_0^1 \int_0^{q_m} 2z\,dz\,dm + \int_0^1 \int_0^{q_m} (2-2z)\,dz\,dm = 4s^*\int_0^1 \int_{q_m}^1 2z\,dz\,dm + 4w^*\int_0^1 \int_{q_m}^1 (2-2z)\,dz\,dm$$

Finally, substituting for *s* using Equation (17) and for *s** using Equation (18) we find that:

(20) $$w^* = \frac{\bar{q}(2-\bar{q})}{4(1-\bar{q})^2}$$

and

(21) $$s^* = \frac{\bar{\theta}^2}{4\left(1-\bar{\theta}\right)^2}$$

The final step before examining the impact of trade opening on income inequality is to solve for the ideal price indices for skilled and for unskilled workers. All products sell at marginal cost. The log price of a product produced in China is $\ln p_{zm} = z\ln s^* + (1-z)\ln w^*, \quad z \in [0,\theta_m]$, while the log-price of a product produced in the US is $\ln p_{zm} = z\ln s, \quad z \in (\theta_m, 1]$. The log aggregate price index for skilled and unskilled workers in industry *m* is given by equations (11) and (12) respectively:

(22) $$\ln P_{Sm} = \int_0^1 2z \ln p_{zm}\,dz = \frac{2}{3}q_m^3 \ln s^* + \left(q_m^2 - \frac{2}{3}q_m^3\right)\ln w^* + \left(\frac{2}{3} - \frac{2}{3}q_m^3\right)\ln s$$

(23)

$$\ln P_{Lm} = \int_0^1 (2 - 2z)\ln p_{zm}\,dz = \left(2q_m^2 - \frac{2}{3}q_m^3\right)\ln s^* + \left(2q_m - q_m^2 + \frac{2}{3}q_m^3\right)\ln w^* + \left(\frac{1}{3} - q_m^2 + \frac{2}{3}q_m^2\right)\ln s$$

We now study the impact of increasing the range of products that China can produce on wages and prices in the US. It is easiest to analyze the case where Chinese production ability increases uniformly in each industry, that is $q_m = q, \forall m$. In this case, the aggregate price indexes $\ln P_S = \int_0^1 \ln P_{Sm}\,dm$ and $\ln P_U = \int_0^1 \ln P_{Um}\,dm$ are equal to the right side of equations (11) and (12) respectively, only dropping the "m" subscript. Starting from 0, a uniform increase in $\theta_m = \theta$ causes the skilled wage in the US to rise relative to unskilled wage.[28] The new Chinese products displace US production of low-quality products that predominantly require unskilled labor, so that the unskilled labor has to be redeployed to producing higher quality goods. However, in contrast to standard models of trade, there is a countervailing force that can offset the rise in the real wage of skilled versus unskilled workers in the US (i.e., $\frac{s/P_s}{w/P_U}$).

Notice that the large labor force in China is devoted to producing only a small share of the total goods in consumption. Since the share of world expenditure on this range of goods is small, Chinese labor is at first very cheap, because its entire labor force must be employed in the production of just a few products. Since these are low-quality products that figure prominently in the expenditures of unskilled workers, the price index for unskilled US workers begins to decline (see Figure A1). The opposite price behavior is experienced by the skilled. As θ rises, the price index for skilled workers begins to rise, driven by the rising wages of the skilled. The figure shows that in this particular specification, the aggregate price index falls as θ rises. In the main text we test the following predictions of the model:

$$\left.\frac{d\ln P_U}{dq}\right|_{q=0} < \left.\frac{d\ln P_S}{dq}\right|_{q=0} \quad and \quad \left.\frac{d\ln P}{dq}\right|_{q=0} < 0.$$

[28] Substituting for s^*, w^* and s using equations (20) and (21) implies that we can express price indices in terms of the exogenous parameter θ.

Adjusting for their respective relative price indices, the real wages of the US unskilled at first improve absolutely and relative to US skilled workers (Figure A2). As θ increases the position of the unskilled in the US begins to turn for the worse - their wages fall more rapidly relative to skilled workers, plus wages in China begin to rise rapidly, pushing up the price of formerly cheap Chinese goods. In this simple model, for small increases of θ from zero the relative real wage of unskilled workers will always *rise*. In the special case depicted in Figure A2, inequality does not fall relative to the pre-trade equilibrium until China produces around half of the goods available in the market.

Figure A1

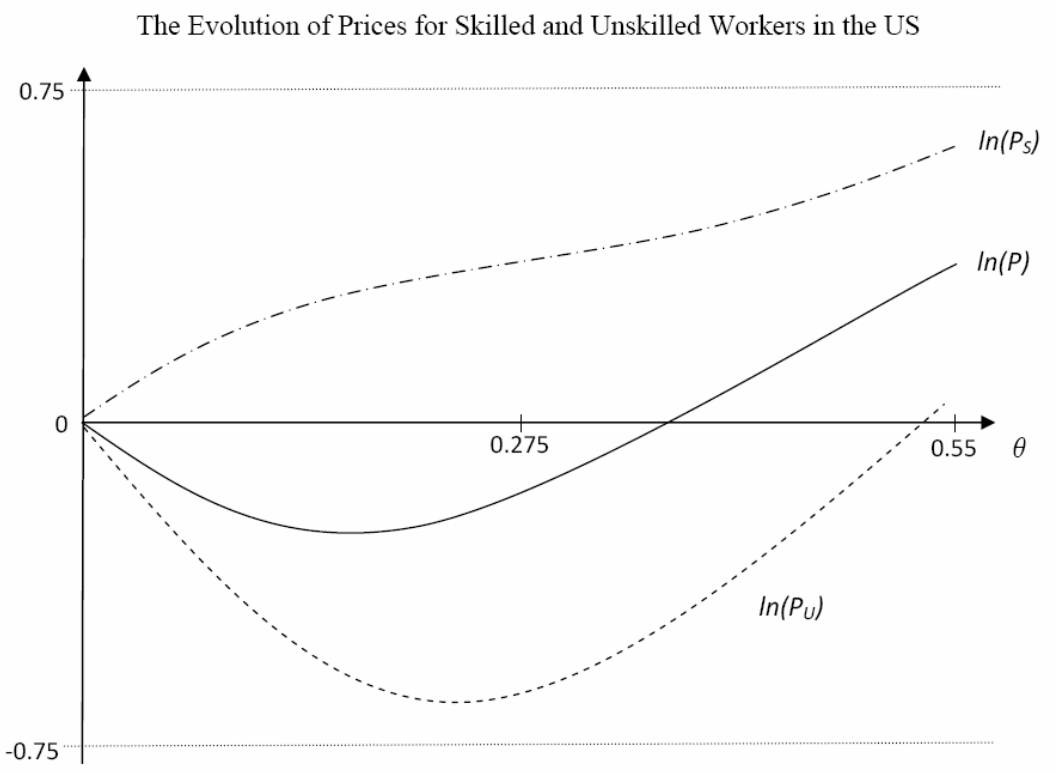
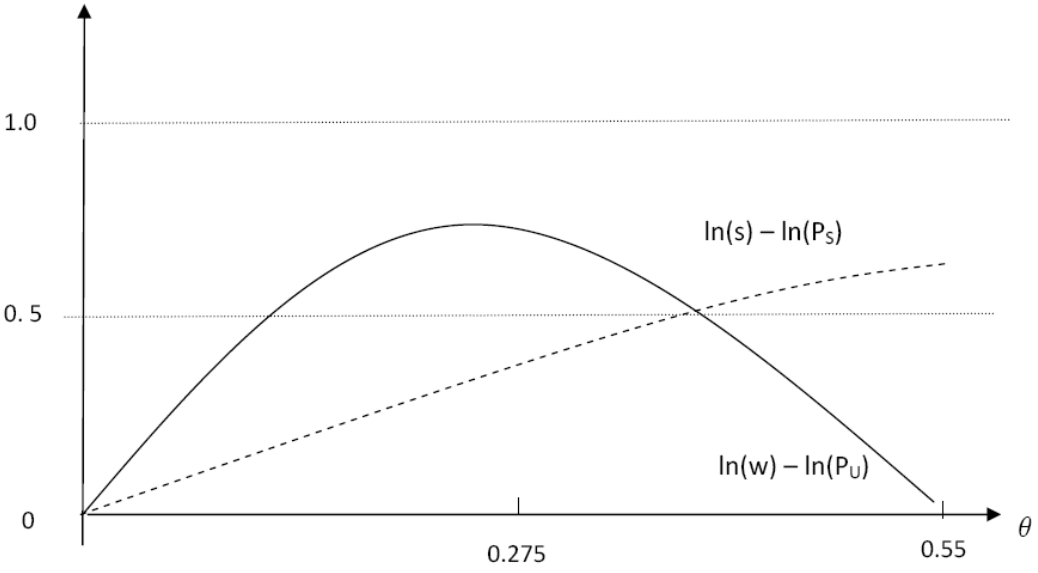


Figure A2



Appendix A: Regressions with Changes in World Export Shares

Appendix Table 4A

The Impact of Changes in Chinese Share on Prices of Non-Durable Goods, 1999 - 2003

	Overall Basket					
	ln (π_m)	ln (π_m)	ln (π_m)	ln ($COLI_m$)	ln ($COLI_m$)	ln ($COLI_m$)
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Developing Share	-0.223			-0.235		
	(5.96)**			[0.043]**		
Change in China Share		-0.747	-0.759		-0.841	-0.86
		[0.113]**	[0.129]**		[0.129]**	[0.148]**
Change in Developing (-ex Asia) Share			0.277			0.18
			[0.159]			[0.186]
Change in Asia Developing (-ex China) Share			-0.034			-0.026
			[0.115]			[0.127]
Constant	0.024	0.036	0.029	0.005	0.02	0.011
	(3.16)**	[0.007]**	[0.007]**	[0.009]	[0.008]*	[0.008]
Observations	604	604	604	605	605	605
R-squared	0.08	0.26	0.28	0.07	0.25	0.28

Robust standard errors in brackets; * significant at 5%; ** significant at 1%

Appendix Table 4B

The Impact of Changes in Chinese Share on Prices of Non-Durable Goods By Income Group, 1999 - 2003

	Poor's Basket				Rich's Basket			
	ln (π_m)	ln (π_m)	ln ($COLI_m$)	ln ($COLI_m$)	ln (π_m)	ln (π_m)	ln ($COLI_m$)	ln ($COLI_m$)
	(1)	(2)	(3)	(4)	(4)	(5)	(6)	(7)
Change in Developing Share	-0.256		-0.53		-0.121		-0.494	
	(4.42)**		[0.092]**		(3.46)**		[0.053]**	
Change in China Share		-0.747		-1.547		-0.474		-1.135
		[0.127]**		[0.237]**		[0.088]**		[0.172]**
Change in Developing (-ex Asia) Share		0.522		0.451		0.19		0.103
		[0.213]*		[0.320]		[0.147]		[0.238]
Change in Asia Developing (-ex China) Share		-0.211		-0.276		-0.01		-0.16
		[0.073]**		[0.202]		[0.051]		[0.139]
Constant	0.039	0.035	-0.053	-0.048	0.03	0.033	-0.066	-0.053
	(4.37)**	[0.009]**	[0.015]**	[0.013]**	(4.60)**	[0.007]**	[0.012]**	[0.011]**
Observations	493	493	527	527	537	537	554	554
R-squared	0.07	0.19	0.12	0.32	0.03	0.1	0.16	0.33

Robust standard errors in brackets; * significant at 5%; ** significant at 1%