The Quality of US Imports and the Consumption Gains from Globalization*

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Abstract

Lack of detailed data on the characteristics and quality of imported goods poses a challenge for measuring consumption gains from rising imports. To tackle this problem, we propose a methodology to infer unobserved quality change using only data on prices and market shares in a differentiated product market. The method identifies a demand system in which product substitutability varies across products based on quantity and quality. We validate the method using data from the US auto market where information on product characteristics and price instruments are available. Without using these additional sources of information, our strategy estimates price elasticities and quality changes in line with the predictions of the standard estimations of BLP demand. We apply this strategy to the US customs data (1989-2006), and find that quality improvements have lowered the price of US imports relative to the CPI by 17%. For comparison, unit values have fallen by around 11% relative to the CPI and increasing variety has contributed an additional 4%. Using a demand system that ignores the heterogeneity in product substitutability leads to a substantial overestimation of the extent of quality improvements.

JEL code: F1, F14, E31

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1 Introduction

Globalization has offered consumers around the world access to a wider variety of products at cheaper prices. We can measure the value of the resulting gains for consumers in a given country using available customs records on the volumes and unit values of each imported product.[1] The data allows us to construct aggregate indices for the price of imported goods that transform the observed changes in the volume and variety of imports into measures of real consumption gain (Feenstra, 1994; Broda and Weinstein, 2006). However, since the available data typically lacks detailed information on product characteristics, we may underestimate the value of imports for consumers if the quality of goods within each product rises over time.[2] More broadly, the problem of accounting for unobserved quality gains applies to many macro settings in which we aim to aggregate observed changes in prices and expenditures across a wide range of goods and services from the perspective of consumers.[3]

The lack of comprehensive measures of quality improvements in traded goods becomes more stark in the face of the vast literature emphasizing the importance of product quality in explaining patterns of trade.[4] As a concrete example for the potential magnitude of the quality channel, consider the rapid growth of US imports from China, where the latter's share in the total volume of US imports grew from around 2% in 1989 to around 15% in 2006. We may expect this rise to stem from the removal of bilateral trade barriers and the productivity gains that lowered the prices of Chinese goods relative to other exporters. Surprisingly, we find that roughly half of the rise in the Chinese share of US imports can be attributed to the set of products whose relative prices have also increased over this period.[5] This fact suggests that quality upgrading in Chinese products, while not reflected in our measures of consumption gains, may have still played a crucial role in their rising appeal for US consumers and importers.

In this paper, we develop and implement a novel strategy to estimate a flexible demand system and to infer product quality from data that only contains information on

[1]Evaluating the magnitude of these consumption gains is particularly important in the face of mounting evidence on sizable adverse effects for domestic workers in import-competing industries (for a review of the evidence, see Autor et al., 2016).

[2]Measures of quality are commonly available only for specific products (e.g., wine as in Crozet et al., 2012). Instead, prior work has mostly relied on unit values (e.g., Schott, 2004a; Hummels and Klenow, 2005), or narrower proxies such as the ISO 9000 management scores (Verhoogen, 2008).

[3]This problem is sometimes referred to as the *quality change bias* in the measures of inflation in the cost-of-living (Boskin et al., 1998; Gordon and Griliches, 1997).

[4]The role of product quality for the patterns of international trade, specialization, and growth has been widely studied in theoretical and empirical work (e.g., Linder, 1961; Flam and Helpman, 1987; Schott, 2004b; Hallak, 2006; Hummels and Klenow, 2005; Verhoogen, 2008; Fajgelbaum et al., 2011; Dingel, 2017).

[5]See Figure 27 and further details and discussions in Appendix D.1.

prices and quantities. We use our method to infer the relative quality changes across all imported varieties and to quantify their contribution to changes in a aggregate price index of US imports. We show that access to better quality products is the primary source of consumption gains from openness in the US over the period 1989-2006, accounting for about 60% of the total decline in relative import prices. Since these quality improvements have remained unmeasured in prior studies, we raise the estimates of consumption gains from US imports over this period to double the size of the available estimates.

Our approach for modeling product quality builds on the standard framework that defines it as residual demand beyond what is explained by the demand function (e.g., Khandelwal, 2010; Hallak and Schott, 2011). This framework requires us to estimate price elasticities, which play a key role in determining both the inferred changes in quality and the value of new varieties to consumers (Broda and Weinstein, 2006; Redding and Weinstein, 2020). The standard approach for estimating these elasticities in trade data (Feenstra, 1994) assumes constant elasticities (CES demand) and imposes uncorrelated product-level supply and demand shocks. However, the latter assumption is untenable if we associate demand shocks with quality. Our strategy circumvents this problem by restricting the dynamics of product-level quality to a Markov process.[6] This leads to moment conditions that allow us to consistently estimate price elasticities in the presence of correlated supply and demand shocks. Moreover, it allows us to consider a broad class of demand systems, including Kimball (1995) demand, that allow for a systematic heterogeneity in price elasticities across products.

Before applying our method to the trade data, we validate its performance in the well studied context of data on prices and market shares of different products in the US automobile market. In this setting, we have two additional sources of information compared to standard international trade data. First, we can use the real exchange rate in the assembly country as an exogenous cost shock instrument in our estimation of the price elasticity. Second, we have detailed product characteristics, including horsepower, miles-per-dollar, and space that we can use as proxies for product quality. In order to assess whether our method delivers reasonable values for the price elasticity, we compare our estimates to alternative instrumental variable approaches and benchmark empirical demand models for differentiated products, such as the random coefficients logit model (Berry, 1994; Berry et al., 1995), which requires the use of both cost shock instruments and product characteristics. We show that our estimated elasticities are in line with those estimated by standard

[6]This strategy has been applied in different settings for demand estimation in the field of IO (e.g., Grennan, 2013; Lee, 2013; Sweeting, 2013). We note that this assumption is also in line with the evidence in Redding and Weinstein (2020) of a strong persistence in their inferred product-level demand shocks.

methods and that our inferred measure of quality is correlated with characteristics valued by consumers.[7] Importantly, when we apply our identification strategy to the Kimball demand system, we uncover variations in price elasticities that are closely in line with those found by the BLP strategy with the random coefficients model.

To use our strategy for measuring consumption gains from rising imports in the US, we assume a nested demand structure in which consumers evaluate the varieties of goods supplied by different countries using a CES or Kimball aggregator. We derive an approximate expression decomposing the gains into the contributions of the fall in the relative price of imports, the rise in quality, and the availability of new varieties, generalizing the results of Feenstra (1994) from CES to Kimball demand with variable elasticities.

We express import prices relative to the US consumer price index (CPI), which we assume adequately accounts for quality changes among domestic producers. We then create a basket of OECD countries as our benchmark for quality, assuming that the quality of the varieties produced by these countries are similar to those of domestic US producers. This allows us to express the quality of the varieties supplied by all other countries relative to this baseline set of products.

In the variable elasticity case, we find that our aggregate index of import prices fell by 32% relative to the US CPI from 1989 to 2006 (1.80% annually), and that quality improvement is the primary contributor to gains from openness. Quality improvement accounts for a cumulative decline of about 17% (0.95% annually) in the aggregate index of import prices, accounting for more than half of the total decline in the price of imports over this period. The remaining part is mostly due to the decline in the relative unit value (unadjusted price) of imported goods, which accounts for an additional 11% cumulative reduction in the aggregate index of import prices (0.60% annually). A smaller role is played by the availability of new varieties, which accounts for a 4.5% cumulative drop in the aggregate index of import prices.[8] Using CES preferences instead of Kimball doubles the gains from openness arising from the product quality channel, largely overstating the quality gains. This confirms the quantitative importance of relaxing the constant elasticity assumption in the standard CES demand systems for evaluating the consumption gains

[7] We use the additional information on product characteristics to directly test our identification assumption. In Appendix B.2, we show that lagged prices are uncorrelated with current product characteristics after controlling for lagged product characteristics. In addition, product characteristics exhibit strong autocorrelations, supporting our Markov process assumption for the dynamics of product-level quality.

[8] Relying on the standard identification approach ruling out correlated supply and demand shocks, Berlingieri et al. (2018) also find that quality change accounts for the bulk of the gains from openness accruing from the trade agreements signed by the EU. Using scanner-level data, Redding and Weinstein (2020) show that the quality bias is sizable relative to the variety bias. Accounting for the additional effect of imports on the consumption of the domestic varieties, Hsieh et al. (2020) find that the increase in imported varieties may be offset by a decrease of domestic varieties based on data from US-Canada trade flows.

from trade.

While relative product quality over the period rose across most non-OCECD countries, we find that quality upgrading among Chinese products is the major driver of the quality gains to consumers in the US. This finding is consistent with the extensive literature on the effects of the economic reforms that China has been undertaking before and since its accession to the WTO.[9]

Prior Work Our paper is related to the literature that attempts to measure the welfare gains from trade liberalization. In a class of trade theories that lead to a gravity structure for trade flows, Arkolakis et al. (2017) show that we can uncover a combined measure of both production and consumption gains based only on the changes in the share of imports in domestic consumption expenditure. This result has inspired much subsequent work within the framework of quantitative trade theories (for a review, see Costinot and Rodríguez-Clare, 2015). While our focus on the consumption side provides an incomplete picture of the overall gains or losses, it averts the need for structural assumptions on the nature of production and leverages the richness of the price data (see also Feenstra and Weinstein, 2017; Berlingieri et al., 2018).[10] We contribute to this literature by accounting for the role of quality and by proposing a novel approach to the estimation of price elasticities that allows for correlations between supply and demand shocks. Our paper is also closely related to Jaravel and Sager (2018) who provide evidence for a substantial effect of trade exposure on consumer prices in the US.

Early empirical work on the importance of quality in trade proxied product quality with unit values (e.g., Schott, 2004b; Hummels and Klenow, 2005). We follow the approach of Khandelwal (2010), Hallak and Schott (2011), and Martin and Mejean (2014) in attributing higher quality to products with higher demand, conditional on prices. Feenstra and Romalis (2014) impose the additional restriction that the income elasticity and the quality of products are systematically related. Our approach is distinguished by our novel strategy for identifying quality and by the generalization of our approach beyond

[9]This result is also consistent with the evidence of the effects of trade liberalization on firm performance. Prior work has documented that a reduction in (input and output) tariffs spurs innovation, productivity and product quality (see Shu and Steinwender (2019) for a survey, and see, among others, Brandt et al., 2017; Fan et al., 2015; Hsieh and Ossa, 2016 for discussions of the specific Chinese case). Schott (2004b, 2008) show that, even if unit values in product-level US import data are higher for advanced economies, Chinese products undertook a rapid process of sophistication. See Appendix D.1 for further discussion.

[10]This insight has recently been used to study the distributional aspects of the consumption gains from trade (e.g., Borusyak and Jaravel, 2018; Adao et al., 2022; Jaravel, 2021). We emphasize that our measures of consumption gains do not provide the full consumption-side welfare effects of rising imports, since the gains due to imports may partly be compensated by a substitution away from domestic consumption (see, e.g., Hsieh et al., 2020).

CES demand systems.

Our paper also contributes to the recent work on the importance of accounting for demand and taste shocks in cost-of-living indices (e.g., Gábor-Tóth and Vermeulen, 2018; Ueda et al., 2019; Redding and Weinstein, 2020). In particular, using US retail scanner data where quality is arguably constant at the barcode-level, Redding and Weinstein (2020) derive a formula for the price index under CES demand that accounts for additional variations in demand due to taste shocks. Our estimation strategy allows us to generalize the application of their approach to settings in which changes in demand partially reflect changes in product quality. We also show that the CES assumption may overstate the contribution of taste shocks to the indices of cost-of-living.

Finally, a growing body of work in trade and macro goes beyond the standard CES assumption and allows for variations in price elasticities through specifications such as Kimball demand to study variable markups and pass-through (e.g., Amiti et al., 2019, Baqaee and Farhi, 2020b, Wang and Werning, 2020).[11] While this literature typically resorts to calibration to match specific moments of interest in the data, we provide a methodology to identify the parameters of Kimball demand using data on observed prices and market shares.

The paper is organized as follow. Section 2 presents the demand system, the corresponding price index, and our econometric approach to identification. Section 3 presents the results of our estimation approach in the benchmark setting of the US automobile market. Section 4 reports our empirical results from the trade data and quantifies the gains from quality. We conclude in Section 5.

2 Theory

We consider the problem of estimating consumer demand in an environment where we only have access to data on prices and quantities (or market shares) for a collection of I products competing in a given market. We observe the sequence $(\boldsymbol{q}_t, \boldsymbol{p}_t)_{t=0}^{T-1}$ where $\boldsymbol{p}_t, \boldsymbol{q}_t \in \{\mathbb{R}_+ \cup 0\}^{|V_t|}$ stand for the vectors of prices and quantities faced and chosen by the consumer, in a potentially changing set V_t of products or varieties (henceforth, we use the terms interchangeably). Crucially, we do not have information on the characteristics

[11] Using alternative deviations from the standard monopolistic competition under CES demand, Feenstra and Weinstein (2017) and Edmond et al. (2015), among others, show that pro-competitive effects of trade liberalization are quantitatively relevant in the US and Taiwan, respectively. Using aggregate trade data does not allow us to directly speak to this margin but our estimation strategy can provide measures of markups if applied at the firm-level. We estimate markups for the US auto market and show that our estimation strategy provides measures of markups that are in line with previous work (Grieco et al., 2021).

of the products or the underlying production costs.

2.1 Demand with Variable Elasticities of Substitution

Let us assume that the observed sequence of quantities and prices are rationalized by Kimball preferences (Kimball, 1995) with a homothetic utility function (aggregator) $q_t \equiv \mathcal{U}(\boldsymbol{q}_t; \boldsymbol{\varphi}_t)$ implicitly defined through:

$$\sum_{i \in V_t} \mathcal{K}\left(e^{\varphi_{it}} \frac{q_{it}}{q_t}\right) = 1, \tag{1}$$

where function $\mathcal{K}(\cdot)$ that satisfies the following conditions:

$$\mathcal{K}(0) = 0, \mathcal{K}(1) = 1, \qquad \mathcal{K}(\cdot), \mathcal{K}'(\cdot) > 0, \qquad \mathcal{K}''(\cdot) < 0.$$

The Kimball aggregator above defines a quantity index q_t that varies linearly in any uniform scaling of demand shifters e^{φ_i} such that $\mathcal{U}\left(e^{\xi}\boldsymbol{q}; \boldsymbol{\varphi}\right) = e^{\xi}\,\mathcal{U}(\boldsymbol{q}; \boldsymbol{\varphi}) = \mathcal{U}(\boldsymbol{q}; \boldsymbol{\varphi} + \xi)$.

Depending on the setting, we may interpret the demand shock $e^{\varphi_{it}}$ in Equation (1) as an unobserved demand shock to the taste for or quality of product i at time t.[12] Since a constant shift ξ in all demand shock parameters φ_{it} keeps the demand unchanged, we normalize the demand shocks by assuming that there exists a set O of base varieties that is observed throughout the entire period, and we set $\sum_{o \in O} \varphi_{ot} = 0$. In the applications covered in this paper, product characteristics are likely to change over time and we will interpret parameters φ_{it} for i as the *(unobserved) quality of good i relative to the average base variety*.

Demand System Solving the expenditure minimization problem for preferences defined in Equation (1), we find that prices and quantities satisfy

$$e^{-\varphi_{it}} \frac{p_{it}}{h_t} = \mathcal{K}'\left(e^{\varphi_{it}} \frac{q_{it}}{q_t}\right), \tag{2}$$

[12] For instance, if we define a product at the level of barcodes in standard scanner data, in which product characteristics remain constant over time, it is reasonable to assume that demand shocks are driven by changes in consumer taste (e.g., Redding and Weinstein, 2020). In other settings in which we define products at more aggregate levels, e.g., at the level of a given product classification code, product characteristics are likely to vary over time, and quality change may be the most likely driver of demand shocks (e.g., Khandelwal, 2010). In the latter case, quality change further includes changes in the contributions of potential changes in the set of varieties within each product classification code as well.

where the h_t is defined as an index that satisfies

$$\sum_{i \in V_t} \mathcal{K}\left(\mathcal{D}\left(e^{-\varphi_{it}} \frac{p_{it}}{h_t}\right)\right) = 1, \tag{3}$$

where we have defined the demand function $\mathcal{D}(\cdot) \equiv (\mathcal{K}')^{-1}(\cdot)$. Defining the normalized quantity $\widetilde{q}_{it} \equiv e^{\varphi_{it}} \frac{q_{it}}{q_t}$ and price $\widetilde{p}_{it} \equiv e^{-\varphi_{it}} \frac{p_{it}}{h_t}$, we can write the demand system in Equation (2) as $\widetilde{p}_{it} = \mathcal{K}'(\widetilde{q}_{it})$ or $\widetilde{q}_{it} = \mathcal{D}(\widetilde{p}_{it})$. Letting $e_t \equiv \sum_{i=0}^{I-1} p_{it} q_{it}$ stand for total consumer expenditure at time t and $s_{it} \equiv \frac{p_{it} q_{it}}{e_t}$ for the expenditure share of good i, we can alternatively express the demand system as[13]

$$s_{it} = \mathcal{S}_i(\widetilde{\boldsymbol{p}}_t) \equiv \frac{\widetilde{p}_{it} \mathcal{D}(\widetilde{p}_{it})}{\sum_{i=0}^{I-1} \widetilde{p}_{it} \mathcal{D}(\widetilde{p}_{it})}. \tag{5}$$

Specifications of the Kimball Function Let us now introduce a number of different parameterizations of the Kimball function. From demand Equation (1), if we fix the index h_t, we can write the own-price elasticity of demand of good i as[14]

$$\sigma_{it} \equiv \left. \frac{\partial \log q_{it}}{\partial \log p_{it}} \right|_{h_t \text{ const.}} = -\frac{1}{\mathcal{E}(\widetilde{q}_{it})}, \tag{6}$$

where we have defined the *Kimball price elasticity* function:

$$\mathcal{E}(\widetilde{q}_{it}) \equiv -\frac{\widetilde{q}\,\mathcal{K}''(\widetilde{q})}{\mathcal{K}'(\widetilde{q})}. \tag{7}$$

Given our assumptions on the Kimball function $\mathcal{K}(\cdot)$, the elasticity function $\mathcal{E}(\cdot)$ is positive everywhere. We may consider additional constraints that imply this function is also nonincreasing and is smaller than unity, implying price elasticities of demand that exceed unity and are nondecreasing in quantity (satisfying Marshall's Second Law of Demand).

We recover standard CES preferences by choosing Kimball function $\mathcal{K}(\widetilde{q}; \varsigma) \equiv \widetilde{q}^{1-1/\sigma}$ in Equation (1) with the corresponding choice of parameterization $\varsigma \equiv (\sigma)$. Below, we consider three additional parametric families of Kimball functions $\mathcal{K}(\cdot; \varsigma)$, each charac-

[13] The dual specification corresponding to Equation (5) is given by

$$s_{it} = \mathcal{S}_i^{\dagger}(\widetilde{\boldsymbol{q}}_t) \equiv \frac{\widetilde{q}_{it} \mathcal{K}'(\widetilde{q}_{it})}{\sum_{i=0}^{I-1} \widetilde{q}_{it} \mathcal{K}'(\widetilde{q}_{it})}. \tag{4}$$

[14] Note that, in principle, the own-price elasticity should additionally account for the effect of change in own-price on the index h_t as well. Under the assumption of monopolistic competition, this additional effect is zero for atomistic producers.

terized by a corresponding family of elasticity functions $\mathcal{E}(\cdot;\varsigma)$.

1. *Klenow and Willis (2006).* This case involves an elasticity function

$$\mathcal{E}(\widetilde{q};\varsigma) \equiv \frac{\widetilde{q}^{\theta}}{\sigma}, \qquad \varsigma \equiv (\sigma, \theta) \tag{8}$$

   that goes from zero (corresponding to infinite price elasticity) to infinity as the normalized quantity goes from zero to infinity.

2. *Finite–Infinite Limits:* This case involves an elasticity function

$$\mathcal{E}(\widetilde{q};\varsigma) \equiv \frac{1}{\sigma + (\sigma_o - \sigma)\,\widetilde{q}^{-\theta}}, \qquad \sigma < \sigma_o,\ \theta > 0,\ \varsigma \equiv (\sigma, \sigma_o, \theta), \tag{9}$$

   that goes from zero (corresponding to infinite price elasticity) to a finite value $1/\sigma$ as the normalized quantity goes from zero to infinity.

3. *Finite–Finite Limits:* This case involves an elasticity function

$$\mathcal{E}(\widetilde{q};\varsigma) \equiv \frac{1}{\sigma_o} + \left(\frac{1}{\sigma} - \frac{1}{\sigma_o}\right)\frac{e^{\theta_o}\widetilde{q}^{\theta}}{1 + e^{\theta_o}\widetilde{q}^{\theta}}, \qquad \sigma < \sigma_o,\ \theta > 0,,\ \varsigma \equiv (\sigma, \sigma_o, \theta, \theta_o), \tag{10}$$

   that goes from a finite value $1/\sigma_o$ to another finite value $1/\sigma$ as the normalized quantity goes from zero to infinity.

In the first and the last cases, the marginal utility of consuming every product at a zero level of consumption ($\widetilde{q}_i = 0$) is infinity. Therefore, the demand takes a finite, nonzero value for every finite value of price. In contrast, in the second case, the marginal utility of consuming every product at a zero level of consumption ($\widetilde{q}_i = 0$) is finite. As a result, there is a finite choke price for any product, above which the consumption falls to zero.

Appendix A.2 derives the family of Kimball functions $\mathcal{K}(\cdot;\varsigma)$ corresponding to each of the three cases above.

2.2 Measuring Welfare Change

To analyze welfare we need to distinguish between the elasticity of the marginal Kimball function, characterized by the price elasticity function $\mathcal{E}$ defined in Equation (7), and the elasticity of the Kimball function, characterized by the *Kimball elasticity* (Dhingra and Morrow, 2019; Baqaee and Farhi, 2020a):

$$\Gamma(\widetilde{q}) \equiv \frac{\widetilde{q}\,\mathcal{K}'(\widetilde{q})}{\mathcal{K}(\widetilde{q})}.$$

Let $\Gamma_{it} \equiv \Gamma\left(\widetilde{q}_{it}\right)$ denote the value of this elasticity for product $i \in V_t$ at time t, and define the *Kimball demand index* $\overline{\Gamma}_t$ as the weighted harmonic mean of this elasticity with weights implied by the expenditure shares of varieties:

$$\overline{\Gamma}_t \equiv \left(\sum_{i \in V_t} s_{it} \, \Gamma_{it}^{-1} \right)^{-1} . \tag{11}$$

Let $E\left(q; \boldsymbol{p}, \boldsymbol{\varphi}\right)$ denote the expenditure function corresponding to the Kimball preferences defined in Equation (1). The Kimball expenditure function satisfies $E\left(q_t; \boldsymbol{p}_t, \boldsymbol{\varphi}_t\right) = p_t \, q_t$, where the the *ideal Kimball price index* is given by:[15]

$$p_t \equiv \sum_i e^{-\varphi_{it}} p_{it} \, \mathcal{D}\left(e^{-\varphi_{it}} \frac{p_{it}}{h_t} \right) = \overline{\Gamma}_t \, h_t, \tag{12}$$

where the index h_t satisfies Equation (3). For instance, under the CES specification, $\mathcal{K}(\widetilde{q}; \sigma) = \widetilde{q}^{1-1/\sigma}$, this elasticity is constant for all varieties and satisfies $\Gamma = 1 - \mathcal{E} = 1 - \frac{1}{\sigma}$.[16] In the CES case, the ideal price index p and the index h are proportional and we do not need to make a distinction between the two. More generally, however, the mean elasticity $\overline{\Gamma}$ gives us a potentially variable wedge between the two indices.

The change in the ideal Kimball price index provides a measure of the change in the expenditure required to achieve a certain level of utility q_t. Such changes are in principle driven by three potential channels: 1) changes in unadjusted unit prices $\boldsymbol{p}_t$, 2) changes in product quality $\boldsymbol{\varphi}_t$, and 3) changes in the set of available products V_t. Here, we provide an approximate decomposition of the changes in the ideal Kimball price index that allows us to gauge the magnitude of the contributions of each of these channels.

Let $V_t^* \equiv V_t \cap V_{t-1}$ denote the common set of products between periods $t-1$ and t, and define the shares of expenditure on this common set of varieties in the two consecutive periods as

$$\Lambda_{t-1}^{+} \equiv \sum_{i \in V_t^*} s_{it-1}, \qquad \Lambda_t^{-} \equiv \sum_{i \in V_t^*} s_{it},$$

Let $s_{it-1}^{+} \equiv s_{it-1} / \Lambda_{t-1}^{+}$ and $s_{it}^{-} = s_{it} / \Lambda_t^{-}$ denote the share of variety i in the set of common varieties in the two periods. Next, define *Kimball Common Varieties (KCV)* demand indices $\overline{\Gamma}_{t-1}^{+}$ and $\overline{\Gamma}_t^{-}$ as the harmonic means of the Kimball elasticity with weights implied by the

[15]See the derivation in Section A.4 of the Appendix.

[16]Note that, in general, the elasticity of the Kimball elasticity function $\Gamma(\cdot)$ is given by $\frac{d \log \Gamma(\widetilde{q})}{d \log \widetilde{q}} = 1 - \mathcal{E}(\widetilde{q}) - \Gamma(\widetilde{q})$, which becomes zero exactly when $\Gamma = 1 - \mathcal{E}$.

expenditure shares within the set of common varieties:

$$\overline{\Gamma}^{+}_{t-1} \equiv \left(\sum_{i \in V_t^*} s^{+}_{it-1} \, \Gamma^{-1}_{it-1} \right)^{-1}, \qquad \overline{\Gamma}^{-}_{t} \equiv \left(\sum_{i \in V_t^*} s^{-}_{it} \, \Gamma^{-1}_{it} \right)^{-1}. \tag{13}$$

Using the definitions above, the following proposition provides an approximation of the decomposition of the change in unit costs in the case of Kimball preferences.

Proposition 1. *To the second order of approximation in $\Delta \equiv \max_{V_{it}^*} |\Delta \log p_{it}|$, the change in the ideal Kimball price index satisfies*[17]

$$\begin{aligned} \Delta \log p_t \approx & \sum_{i \in V_t^*} s^*_{it,T} \, \Delta \log p_{it} - \sum_{i \in V_t^*} s^*_{it,T} \, \Delta \varphi_{it} \\ & + \left(\frac{1 - \overline{\Gamma}^*_t}{\overline{\Gamma}^*_t} \right) \log \left(\frac{\Lambda^-_t}{\Lambda^+_{t-1}} \right) + \frac{1}{\overline{\Gamma}^*_t} \left(\log \left(\frac{\overline{\Gamma}_t}{\overline{\Gamma}_{t-1}} \right) - \log \left(\frac{\overline{\Gamma}^-_t}{\overline{\Gamma}^+_{t-1}} \right) \right), \end{aligned} \tag{14}$$

where $s^*_{it,T} \equiv \frac{1}{2}(s^+_{it-1} + s^-_{it})$ stands for the Törnqvist weight of product i within the set of common varieties, and where we have defined the between-period mean of the KCV demand indices $\overline{\Gamma}^*_t \equiv \frac{1}{2}\left(\overline{\Gamma}^+_{t-1} + \overline{\Gamma}^-_t\right)$.

Proof. See Appendix A.4. □

The first two terms on the right hand side of Equation (14), the Törnqvist-weighted mean changes in prices (the Törnqvist price index) and quality, account for the contributions of unadjusted price and quality changes, respectively. The remaining terms, on the second line of Equation (14), account for the effect of changes in the set of available products.

To better understand this result, let us consider the special case of the CES aggregator, corresponding to the Kimabll function $\mathcal{K}(\widetilde{q};\sigma) = \widetilde{q}^{1-1/\sigma}$. In this case, we have $\overline{\Gamma}_t = \overline{\Gamma}^-_t = \overline{\Gamma}^+_{t-1} = 1 - \frac{1}{\sigma}$ for all t, which leads to the approximate decomposition

$$\Delta \log p_t \approx \sum_{i \in V_t^*} s^*_{it,T} \, \Delta \log p_{it} - \sum_{i \in V_t^*} s^*_{it,T} \, \Delta \varphi_{it} + \frac{1}{\sigma - 1} \log \left(\frac{\Lambda^-_t}{\Lambda^+_{t-1}} \right). \tag{15}$$

In this particular case, prior work has provided us with an exact decomposition of the change in the ideal price index to components accounting for the contributions of the

[17] The proof of the proposition provides a more refined approximation that showcases the additional role of the third order terms.

changes in price, quality, and variety (Feenstra, 1994; Broda and Weinstein, 2006; Redding and Weinstein, 2020):

$$\Delta \log p_t = \sum_{i \in V_t^*} s_{it,SV}^* \, \Delta \log p_{it} - \sum_{i \in V_t^*} s_{it,SV}^* \, \Delta \varphi_{it} + \frac{1}{\sigma - 1} \log \left(\frac{\Lambda_t^-}{\Lambda_{t-1}^+} \right), \tag{16}$$

where we have defined the Sato-Vartia weights $s_{it,SV}^* \propto \frac{s_{it}^- - s_{i-1}^+}{\log(s_{it}^- / s_{it-1}^+)}$ on the set of common varieties. Whereas the exact decomposition in Equation (16) uses the Sato-Vartia price and quality indices to measure the contribution of quality-adjusted price and quality, the approximate expression uses the Törnqvist indices.[18] The third term in both equations represents the Feenstra (1994) correction and captures the contribution of new and disappearing varieties.

Comparing Equation (14) with the CES case in Equation (16), we find two differences in accounting for the contribution of new varieties. First, whereas the growth in the expenditure share of common varieties is multiplied in the CES case by a factor $\frac{1}{\sigma-1}$ involving the elasticity of substitution, more generally it is multiplied by a factor $\frac{1-\overline{\Gamma}_t^*}{\overline{\Gamma}_t^*}$, which depends on the Kimball demand index on the set of common varieties . In addition, we also have to account for the potential gap in the growth of the Kimball demand index across all and across common varieties, as captured by the last term on the right hand side of Equation (14).

The expressions for the contribution of quality are identical between the ideal Kimball price index in Equation (14) and the exact CES price index in Equation (16). However, in practice we need to infer the unobserved quality changes $\Delta \varphi_{it}$ based on our assumption about the demand system.[19] What happens if we misspecify the underlying Kimball preferences to be CES? The next proposition compares the contribution of quality changes under CES and Kimball.

Proposition 2. *Consider using a misspecified CES demand system with elasticity of substitution σ^{ces} to infer quality φ_{it}^{ces} based on observed sequences of prices and quantities that are rationalized*

[18] Using the expression for CES demand, we can write $\Delta \log s_{it}^* + \Delta \lambda_t = (1-\sigma)(\Delta \log p_{it} - \Delta \varphi_{it} - \Delta \log p_t)$ where we have defined $\Delta \log s_{it}^* \equiv \log(s_{it}^- / s_{it-1}^+)$ and $\Delta \lambda_t \equiv \log(\Lambda_t^- / \Lambda_{t-1}^+)$. Take the mean of both sides using Törnqvist weights, we find that the residual error in Equation (15) is simply given by the Törnqvist-weighted mean of $\Delta \log s_{it}^*$ across the set of common varieties, which is zero to the second order of approximation. More generally, the Törnqvist index provides a second order approximation to changes in the unit cost for any smooth utility function (Jaravel and Lashkari, 2021).

[19] Redding and Weinstein (2020) show that we can rewrite Equation (16) directly in terms of observable changes and the elasticity of substitution σ. Following the logic of foonote 18, we can combine $\Delta \log s_{it}^* + \Delta \lambda_t = (1-\sigma)(\Delta \log p_{it} - \Delta \varphi_{it} - \Delta \log p_t)$ and the assumption $\frac{1}{|O|} \sum_{o \in O} \varphi_{ot} = 0$ to find $\Delta \log p_t = \frac{1}{|O|} \sum_{o \in O} \Delta \log p_{it} + \frac{1}{\sigma - 1} \left(\frac{1}{|O|} \sum_{o \in O} \Delta \log s_{ot}^* + \Delta \lambda_t \right)$.

by an underlying Kimball demand system. The gap between the true and the misspecified measures of quality change is approximately given by

$$\sum_{i\in V_t^*} s_{it,T}^*\left(\Delta\varphi_{it}-\Delta\varphi_{it}^{ces}\right)\approx\frac{1}{|O|}\sum_{o\in O}\left(\frac{1}{\sigma^{ces}-1}-\frac{1}{\sigma_{ot}-1}\right)\log\left(\frac{s_{ot}^-}{s_{ot-1}^+}\right)+\sum_{i\in V_t^*} s_{it,T}^*\frac{1}{\sigma_{it}-1}\log\left(\frac{s_{it}^-}{s_{it-1}^+}\right)$$
$$+\left(\sum_{i\in V_t^*} s_{it,T}^*\frac{1}{\sigma_{it}-1}-\frac{1}{|O|}\sum_{o\in O}\frac{1}{\sigma_{ot}-1}\right)\left[\log\left(\frac{\Lambda_t^-}{\Lambda_{t-1}^+}\right)+\log\left(\frac{\bar{\Gamma}_t}{\bar{\Gamma}_{t-1}}\right)\right], \tag{17}$$

where, as before, $s_{it,T}^*\equiv\frac{1}{2}(s_{it-1}^+ + s_{it}^-)$ *stands for the Törnqvist weight of product* i *within the set of common varieties, and where* σ_{it} *is the own-price elasticity given by Equation (6).*

Proof. See Appendix A.4. □

The first term on the right hand side of Equation (17) depends on the gap in the love-of-variety proxies measured by the CES and Kimball own-price elasticities and the growth in expenditure shares. For instance, if the CES estimate of own-price elasticity is lower than that of Kimball, and thus the measure of love of variety $\frac{1}{\sigma-1}$ exceeds the average of the Kimball proxies $\frac{1}{\sigma_{ot}-1}$, the contribution of this term is negative or positive, depending on whether the shares of base products in the common set falls or rises. The second term accounts for the contribution of reallocations of expenditure across products and the heterogeneity in own-price elasticities. Under Kimball, we infer higher quality change if expenditure shifts toward products with lower price elasticities. Finally, the last term, on the second line of Equation (17), accounts for the gap between the love-of-variety proxies between the common set V_t^* and the base set O of products. If the underlying demand is indeed CES, then both the second and the third term are always zero since the own-price elasticities are constant at $\sigma_{it}\equiv\sigma$.

2.3 The Dynamic Panel Approach to Demand Estimation

Consider a family of Kimball functions $\mathcal{K}(\cdot;\varsigma)$ parameterized with a vector ς of parameters. Following from our assumptions about the Kimball function, Equation (5) defines a demand system $s_{it}=\mathcal{S}_i(\widetilde{\boldsymbol{p}}_t;\varsigma)$, which is invertible in the subsect of products within the set V_t. Without loss of generality, for the purpose of estimation we may consider a singleton base set $O\equiv\{o\}$ with a base product $o\in V_t$ for all t. For any product $i\in V_t$ at time t, we can then write $\log p_{it}=\log\mathcal{S}_i^{-1}(\boldsymbol{s}_t;\varsigma)+\log h_t+\varphi_{it}$, where h_t satisfies Equation (3). Using the normalization $\varphi_{ot}=0$ to substitute for h_t, we can derive a relationship of the form

$$\log p_{it} = \pi_i \left(\boldsymbol{s}_t, p_{ot}; \boldsymbol{\varsigma} \right) + \varphi_{it}, \qquad i \in V_t / O, \tag{18}$$

for an implicit function π_i between the log price and the demand shock for each non-base product, on the one hand, and the vector of expenditure shares and the log price of the base good, on the other.

Equation (18) offers a parametrized demand function that may be estimated in the data. Needless to say, the key challenge for the identification of this demand system is the potential correlation between the demand shock, log price, and the expenditure shares. We now turn to our approach for tackling this problem.

Our approach begins by imposing a restriction on the dynamcis of demand shocks, expressed in the following assumption.

Assumption 1 (Dynamics of Demand Shocks)**.** *The following Markov process governs the demand shocks φ_{it} for product i at time t:*

$$\varphi_{it} = g_i \left(\varphi_{it-1}; \boldsymbol{\varrho} \right) + u_{it}, \tag{19}$$

where u_{it} is a zero-mean i.i.d innovation to the demand shock and where $\boldsymbol{\varrho}$ is a vector of paramters characterizing the persistence of the demand shock process.[20]

Equation (19) implies that despite potential persistence in the process of demand shocks, they are not completely predictable based on past realizations. In our baseline model, we assume that the demand shock process is a stationary AR(1) process with a product-specific mean:[21]

$$g_i \left(\varphi_{it-1}; \boldsymbol{\varrho} \right) \equiv \rho \varphi_{it-1} + (1 - \rho) \phi_i, \tag{20}$$

where $\boldsymbol{\varrho} \equiv (\rho, \phi)$ is the vector of the parameters of the Markov process.

We next make our main identification assumption, which rules out the dependence of past decisions by firms and consumers on the current innovation to the demand shock.

Assumption 2 (Identification Assumptions)**.** *When firms and consumers choose prices and quantities for each product at time t, their decisions do not depend on the future innovations to the demand shock, in the sense that the latter is uncorrelated with different moments of lagged log*

[20]Note that we can generalize this condition to higher order Markov dynamics, for instance, assuming $\varphi_{it} = g_i \left(\varphi_{it-1}, \varphi_{it-2}, \cdots; \boldsymbol{\varrho} \right) + u_{it}$, where the contemporaneous demand shock further depends on its higher-order lags.

[21]This model can also account for a process with stationary growth, e.g., a model with $g_i \left(\varphi_{it-1} \right) \equiv \varphi_{it-1} + \gamma_i$, in the limit $\rho \to 1$ such that $\phi_i \equiv \gamma_i / \left(1 - \rho \right) \to \infty$.

price and log quanty:

$$\mathbb{E}\left[u_{it}\middle|\left(\log p_{it-\tau}\right)^m,\left(\log q_{it-\tau}\right)^m\right]=0,\qquad \tau\geq 1,\tag{21}$$

where $m \geq 1$ *. Moreover, we assume that the log price process has a nonzero autocorrelation* $\mathbb{E}\left[\log p_{it}\log p_{it-1}\right]\neq 0$.

In combination with Equation (19), we can use Equation (21) to derive different sets of orthogonality conditions that allow us to estimate the vector of parameters ς. As an example, if we simply consider $m=1$ in Equation (21), we can find orthgonality conditions $\mathbb{E}\left[u_{it}\middle|\log p_{it-1}\right]=0$, $\mathbb{E}\left[u_{it}\middle|\log q_{it-1}\right]=0$, $\mathbb{E}\left[u_{it}|\varphi_{it-1}\right]=0$, and $\mathbb{E}\left[u_{it}\right]=0$ for each product i and each time t.

Then, we can substitute Equation (19) for the demand shock φ_{it} in Equation (18) to find

$$\log p_{it}-\pi_i\left(\boldsymbol{s}_t,p_{ot};\varsigma\right)-g_i\left(\log p_{it-1}-\pi_i\left(\boldsymbol{s}_{t-1},p_{ot-1};\varsigma\right);\boldsymbol{\varrho}\right)=u_{it}.\tag{22}$$

Using this expression for the demand shock innovation u_{it} in Equation (21) yields the desired moment conditions. The assumption of nonzero autocorrelation ensures that the lagged values of log price and log quantity offers meaningful instruments for the corresponding contemporaneous values of the same variables.

Moment Conditions For each of the three Kimball specifications defined by Equations (8)–(10), Appendix A.3 presents a simple scheme that allows to invert the demand function (5) to find the corresponding inverted demand function π_i in Equation (18). We can then write the corresponding moment conditions

$$\mathbb{E}\left[\left(\log p_{it}-\pi_i\left(\boldsymbol{s}_t,p_{ot};\varsigma\right)-g_i\left(\log p_{it-1}-\pi_i\left(\boldsymbol{s}_{t-1},p_{ot-1};\varsigma\right);\,\boldsymbol{\varrho}\right)\right)\times z_{it}\right]=0,\tag{23}$$

where the instruments z_{it} include lagged values of log prices, log quantities, and both variables squared (corresponding to the case of $m=2$ in Equation (21)), in additional to lagged demand shocks and time and product dummies. We include the squared values of lagged log price and log quantity since in this case our identification aims to characterize the variations in price elasticity as a function of quantity.

2.3.1 CES Demand

In the CES case, we can derive a simple expression for the inverse demand function π_i in Equation (18). It is easy to see that in Equation (3), we find $\mathcal{D}(\widetilde{p})=\widetilde{p}^{-\sigma}$. From Equation

(5) and the assumption $\varphi_{ot} = 0$, we find that the logarithm of the expenditure share of the base good satisfies $\log s_{ot} = (1-\sigma)(\log p_{ot} - \log h_t)$. This allows us to write the demand shock for good i at time t as:

$$\varphi_{it} = \log\left(\frac{p_{it}}{p_{ot}}\right) + \frac{1}{\sigma-1}\log\left(\frac{s_{it}}{s_{ot}}\right), \tag{24}$$

implying an inverted demand function $\pi_i(\boldsymbol{s}_t, p_{ot}; \sigma) \equiv \log p_{ot} + (\log s_{it} - \log s_{ot})/(\sigma-1)$ in Equation (18).

Combining the expression in Equation (24) for the demand shock with Equations (22) and (21) provides us with the following set of moment conditions:

$$\mathbb{E}\left[\left(\log\left(\frac{p_{it}}{p_{ot}}\right) + \frac{1}{\sigma-1}\log\left(\frac{s_{it}}{s_{ot}}\right) - g_i\left(\log\left(\frac{p_{it-1}}{p_{ot-1}}\right) + \frac{1}{\sigma-1}\log\left(\frac{s_{it-1}}{s_{ot-1}}\right); \boldsymbol{\varrho}\right)\right) \times z_{it}\right] = 0, \tag{25}$$

where the instruments z_{it} include different functions of lagged quantities, prices, and demand shocks, as well as product and time dummies. The moment conditions above allow us to estimate demand elasticity parameter σ and the demand shock process parameters $\boldsymbol{\varrho}$.

To be more specific, consider the AR(1) assumption in Equation (20). In this case, we can rely on the log-linearity of the model and write the moment conditions in first-differences:

$$\mathbb{E}\left[\left(\Delta\log\left(\frac{p_{it}}{p_{ot}}\right) + \frac{1}{\sigma-1}\Delta\log\left(\frac{s_{it}}{s_{ot}}\right) - \rho\left(\Delta\log\left(\frac{p_{it-1}}{p_{ot-1}}\right) + \frac{1}{\sigma-1}\Delta\log\left(\frac{s_{it-1}}{s_{ot-1}}\right)\right)\right) \times z_{it}\right] = 0, \tag{26}$$

where $\Delta \log x_{it} \equiv \log x_{it} - \log x_{it-1}$, and the instruments now z_{it} include *double* lagged log prices, log quantities, demand shocks, in addition to the time and product dummies, corresponding to the case of $m = 1$ in Equation (21). In this case, we can identify the demand elasticity parameter σ and the demand shock persistence ρ without the need to estimate the long-run mean of product-level demand shocks ϕ in Equation (20).

2.3.2 Discussion

The Logic of Identification To gain some intuitions about the assumption in Equation (21), let us consider an explicit model of firm price setting that satisfies this assumption. Consider the standard environment in which firms flexibly set prices and thus choose them to maximize contemporaneous profits. In this case, the price at a given point in time should only depend on the current variables, and should not depend on the firm's information or forecasts about future product demand and quality. More specifically, this scenario leads to the following process for the evolution of log prices:

$$\log p_{it} = \log mc_i\left(q_{it}, \varphi_{it}, w_{it}\right) + \log \mu_i\left(\boldsymbol{p}_t, \boldsymbol{q}_t, \boldsymbol{\varphi}_t\right) + v_{it}, \tag{27}$$

where $mc_i\left(\cdot,\cdot,\cdot\right)$ is the marginal cost function, which may depend on quantity q_{it}, quality φ_{it}, and exogenous cost shifters w_{it}, $\mu_i\left(\cdot,\cdot,\cdot\right)$ is the log markup function, which may depend on the vector of current prices $\boldsymbol{p}_t$, quantities $\boldsymbol{q}_t$, and demand shocks $\boldsymbol{\varphi}_t$ of all products in the market, and where v_{it} is the residual error that is uncorrelated with all other variables of interest. The price setting Equation (27) satisfies Equation (21) even if the firm does indeed have some information about the future demand shock innovation.[22]

More generally, we can consider a model of dyanmic price setting in which the log price additionally depends the expected value of future cost and demand shocks, as well as those of the competitors, conditional on the information set $\mathcal{I}_{it}$ of the firm at that moment in time. In this case, it is sufficient to assume that the firm does not know the future demand shock innovation $u_{it} \notin \mathcal{I}_{it}$ to again satisfy the assumption in Equation (21). Regardless of the underlying model of price setting, the orthogonality assumption allows us to rule out a *direct* functional dependence of the price p_{it} on the future demand shocks φ_{it+1}. Thus, all systematic correlations between log price and the future demand shocks φ_{it+1} are driven by the persistence of the demand shock process φ_{it}.

Comparison with Alternative Approaches to Identification The standard approach to the identification is to use exogneous cost shifters w_{it} that affect prices according to Equation (27) as instruments in Equation (18). As already mentioned, we are interested in settings where we only have access to information on prices and quantities. Our identification assumption allows us to use the lagged values of price as an instrument for current price, after controlling for the expectation of the demand shock conditional on lagged prices. However, we also emphasize that most cost shock instruments used in practice affect the price or costs of specific inputs. To the extent that in response to these shocks firms substitute away or toward those inputs, it is likely that such substitution may additionally affect product quality, thereby violating the exogeneity of some cost shock instruments.

Finally, the conventional approach to estimating demand in the absence of cost shock

[22]Note that under the assumption of flexible pricing, our identification assumption is weaker compared to the typical assumptions in the application of the dynamic panel methods to production function estimation (see Ackerberg, 2016). In particular, we do not require the assumption that the innovation u_{it} does not belong to the information set of the firm at time $t-1$. With flexible pricing, even if the firm knows its future demand shock, it does not have an incentive to reflect that in its current pricing decision.

instruments is the Feenstra (1994) method that crucially rules out correlations between demand shocks φ_{it} and any shocks to prices that are not driven by quantity changes. In particular, any dependence of the marginal cost on quality in Equation (27), i.e., $\frac{\partial \log mc}{\partial \varphi} \neq 0$, violates this assumption. Intuitively, we expect improvements in quality to be associated with more costly inputs, making it likely that this assumption is indeed violated in practice. Section A.6 in Appendix A provides a detailed discussion of how our assumptions on the dynamics of demand shocks allows us to estimate demand without the need of the identification assumption of Feenstra (1994).

3 Validating the Strategy using US Auto Data

In this section, we apply the Dynamic Panel approach, henceforth DP, for demand estimation to detailed data on the US automobile market and compare the resulting estimates with those found using benchmark methods of demand estimation including the random coefficient logit model (Berry, 1994; Berry et al., 1995).

3.1 Data

We use data on the US automobile market from 1980 to 2018. The Wards Automotive Yearbooks contain information on specifications, list prices and sales by model for all cars, light trucks, and vans sold in the US.[23] Vehicle characteristics include horsepower, miles-per-dollar, miles-per-gallon, weight, width, height, style (car, truck, SUV, van, sport), and producer. Additional information such as the producer's region, whether the model is an electric vehicle, a luxurious brand, or a new design (redesign), complement the data from the yearbooks.[24] We perform standard cleaning to the data following Grieco et al. (2021) and Berry et al. (1995), and, in addition, we exclude models that have an average price higher than $100k over the entire time period and drop observations with a change in market share above (below) the 99th (1th) percentile within each year.[25]

We follow Grieco et al. (2021) and Goldberg and Verboven (2001) in the construction of an exogenous instrument for prices based on exchange rates. We use the lagged bilateral real exchange rate between the US and the country of assembly of each model, henceforth

[23]The Wards Automotive Yearbooks contain information for all trims (variants) of each model. Following standard practice, we aggregate all information at the model level based on the median across trims (Berry et al., 1995; Grieco et al., 2021).

[24]Table 6 in Appendix B.1 provides additional details and displays summary statistics for our sample.

[25]As in Berry et al. (1995), we define the new variable "space" as the product between length and width and exclude observations with a value larger than 6. Similarly, we define the ratio of horsepower per 10lbs and exclude observations with a value larger than 3.

RER.[26] RER constitutes an arguably exogenous shifter of production costs capturing, in part, local labor market conditions in the country of assembly. This is because exogenous changes in local wages are reflected on the local price level and, in turn, on the real exchange rate. In addition, exogenous movements in the nominal exchange rate between the US and the country of assembly represents another source of variation for the RER as firms can lower their prices when the local currency depreciates.

3.2 Benchmark Empirical Models

Our goal is to examine two distinct aspects of the approach we proposed in Section 2: the effectiveness of the DP approach as an identification strategy, and the ability of the Kimball demand system to provide a satisfactory account of heterogeneity in price elasticities. First, to study the identification aspects, we estimate a standard CES specification using the DP approach and compare it against the standard instrumental variable approach that uses cost shocks (RER). In the latter case, we take advantage of the information on product characteristics to directly proxy for product quality. Second, to study the properties of the Kimball specification, we compare it against the current workhorse demand model for differentiated products, i.e., the random coefficient logit model (Berry, 1994; Berry et al., 1995). In this exercise, we also compare the estimates of the Kimball specification using the two alternative identification strategies: the DP approach and the standard cost shock IV approach. Below, we discuss the details of these alternative benchmark models.

To study the properties of the DP identification strategy, we consider the CES specification that leads to a simple log-linear relationship between market shares and prices to estimate the elasticity of susbsitution σ:

$$\log s_{it} = -(\sigma - 1)\, \log p_{it} + \beta \boldsymbol{x}_{it} + make_i + \delta_t + \epsilon_{it}, \tag{28}$$

where $make_i$ specifies the producer of product i. Here, $\boldsymbol{x}_{it}$ stands for the vector of product characteristics, including space, horsepower, miles-per-dollar, luxury brand, vehicle type (sport, electric, truck, suv, van). As mentioned, we can address the endogeneity of prices using a proxy for the costs of production, the real exchange rate (RER) in the assembly country, as a price instrument and also controlling for product characteristics and time and producer fixed effects. We also estimate the specification in Equation (28) using ordinary least squares, as an additional benchmark for the instrumented regressions.

[26] The RER is constructed as the ratio of the expenditure price levels between the assembly country and the US. The expenditure price levels are available from the Penn World Tables. See Grieco et al. (2021) for additional details.

We also estimate Equation (28) with the DP approach, using the moment conditions in first-differences as in Equation (26) and relying on double-lagged prices and market shares as instruments, together with time fixed effects. In this case, we use the Chevrolet Corvette model as the reference product for the estimation. However, for all welfare calculations, the measure of inferred quality is normalized such that the average change in quality of the set of continuing models that are not redesigned is zero (Grieco et al., 2021).[27]

As mentioned, we next compare our Kimball specification against the empirical discrete choice model of differentiated products presented in Berry (1994) and Berry et al. (1995) (henceforth BLP). The BLP method assumes heterogeneous consumers, whereby the utility u_{nit} of consumer n for a product i with the vector $\boldsymbol{x}_{it}$ of product characteristics is given by $u_{nit} = \alpha\, p_{it} + \beta\, \boldsymbol{x}_{it} + \alpha_n p_{it} + \beta_n \boldsymbol{x}_{it} + \epsilon_{nit}$, where the consumer-specific coefficients α_n and β_{nk} on price and characteristic k, respectively, are zero-mean, gaussian-distributed, *i.i.d.* sources of unobserved heterogeneity in consumer taste. Following standard practice, we normalize to zero the utility of the outside option to not purchase any available model. We estimate the random coefficients model including the same set of product characteristics as in the CES specification, using the RER as a cost-shock instrument, and following the best practices as in Conlon and Gortmaker (2020).

Finally, we estimate the three parametric families of Kimball functions presented in Equations (10), (9) and (8), using the moment condition in Equation (23). We estimate the Kimball specification using both the DP identification strategy and the RER as a cost-shock instrument. Here, too, we choose the Chevrolet Corvette as reference product for the estimation while quality is normalized with respect to the set of continuing models that are not redesigned. For the DP case, we use lagged prices and their quadratic powers as instruments, as well as time and producer fixed effects. For the standard IV approach, we use RER, log(RER) and their powers as instrument.

3.3 The Comparison of Estimated Own-Price Elasticities

In Table 1, we report the estimated price elasticities found by the different approaches for the whole sample. The first three columns show the estimated price elasticity under the CES specification using OLS estimation, using the RER variable as the cost shock instrument (IV henceforth), and using our DP approach. The remaining four columns display different moments of the distribution of the estimated own-price elasticities under the two models with variable elasticities, the BLP and the Kimball specifications. In the latter

[27] For the set O of continuing models that are not redesigned, $\frac{1}{|O|}\sum_{o \in O} \Delta\varphi_{ot} = 0$.

case, the table also shows the estimates when using the RER as the cost shock instrument and when using our DP approach.

As expected, we find that the OLS estimate of the CES price elasticity displays a bias towards zero due to the positive correlation between demand and price shocks, despite the fact that our specification includes product characteristics to control for quality. When we use the cost shock instrument, the magnitude of the estimated CES elasticity rises relative to its OLS counterpart (1.98 from 4.64). The latter estimates suffer from downward bias due to correlation between prices and demand shocks. This result confirms the need for price instruments to correct for the endogeneity bias in this setting.

Importantly, applying the DP approach to the CES specification delivers a CES elasticity of substitution of 4.25, close to the estimated elasticity obtained with the cost shock instrument. This suggests that our DP approach provides a solution for the endogeneity problem without relying on additional costs shocks, and even without controlling for product characteristics.

How important is accounting for heterogeneity in price elasticities? Comparing the estimates under the CES and the BLP models, we find that ignoring the heterogeneity in price elasticities leads to a bias toward zero under the former. The median, the unweighted, and the weighted means of the estimated elasticities are larger under the BLP specification compared to the CES. Despite its simplicity, the Kimball specification also appears to allow for sufficient heterogeneity to circumvent this problem: all three moments of the distributions of the estimated own-price elasticities under Kimball are closer to the those under BLP, when compared to those of CES. Moreover, we again find that the Kimball estimates found using the cost shock instrument and using the DP approach are close, providing additional evidence of the validity of the DP approach.[28]

We next explore the relationship between the volume of sales and the estimated elasticities across products under the BLP and the Kimball models. The left panel of Figure 1 shows that this relationship is similar between the BLP specification and the Kimball specification, when estimated under both identification strategies (DP and IV). This result confirms that the Kimball specification can indeed account for the same relationship between sales and price elasticity as that uncovered by the BLP specification, both qualitatively and quantitatively, and that the DP approach can identify this pattern without the use of any additional information other than prices and market shares.

The right panel of Figure 1 shows that the entire distribution of elasticities estimated by the BLP method is similar to those estimated under the different Kimball specifications

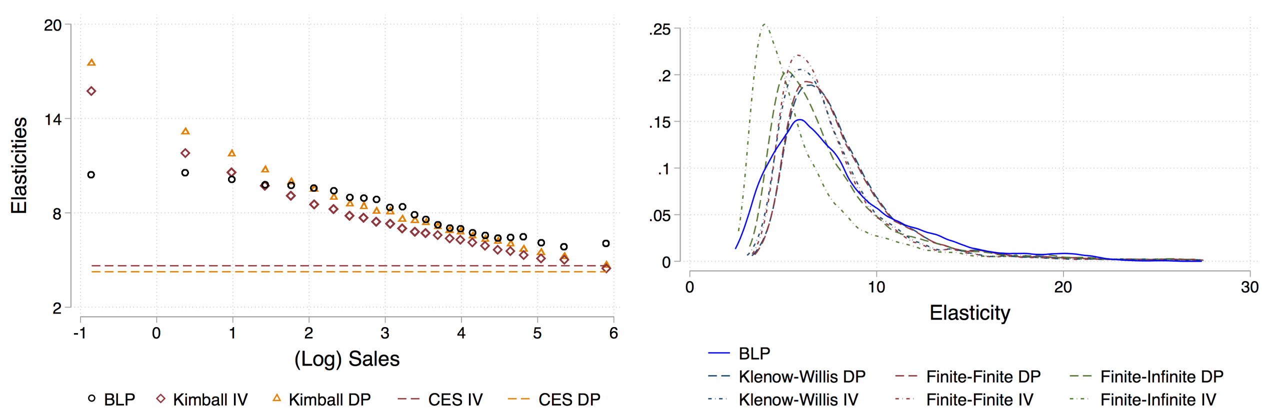
[28] Tables 8 and 9 in Appendix B.3 report the estimated BLP coefficients and the estimated Kimball parameters, respectively.

Table 1: Price Elasticity

	CES				Kimball	
	OLS	IV	DP	BLP	IV	DP
Mean	1.979	4.637	4.254	7.618	7.862	8.581
	(0.200)	(1.135)	(1.647)	(0.442)	(1.472)	(1.368)
Median				6.706	6.793	7.419
				(0.389)	(1.008)	(1.010)
Weighted Mean				6.890	5.462	5.839
				(0.364)	(0.641)	(0.890)
IQR				4.063	2.929	3.366
				(0.240)	(0.843)	(0.966)

Note: The table reports the estimated own-price elasticities for the full sample. Each column corresponds to a different econometric model: CES OLS, CES IV, CES DP, BLP, Kimball IV, and Kimball DP. For the CES cases, we report the own-price elasticity while for the VES cases (BLP and Kimball) we report a set of moments from the distribution of the estimated price elasticities. For the BLP and the Kimball specifications, we report the mean and the median elasticity together with the expenditure weighted mean elasticity and the interquartile range. For each coefficient we report the 95% confidence intervals. For the CES specifications, standard errors are clustered at product (model) level. The standard errors of the statistics for the Kimball specfcations are obtained from N=100 bootstrapped samples (using models as resampling unit). Due to computational limitations, we follow Conlon and Gortmaker (2020) in copmuting standard errors for the BLP statistics from a parametric bootstrap procedure (we draw 100 different sets of coefficients from the estimated joint distribution of parameters and compute the median under each of these parametric bootstrap samples).

Figure 1: Elasticity Heterogeneity in Kimball and BLP



Note: The left panel plots a binscatter representation of the relationship between (log) sales and the estimated elasticity of substitution. Products with (log) sales less than -1 are dropped. We consider the set of elasticities estimated from: i) the BLP model; ii) the Finite-Finite Kimball model using cost shocks (RER) as instruments (Kimball IV); iii) the Finite-Finite Kimball model using the DP approach (Kimball DP). We also report the CES elasticity estimated using IV and DP. The right panel shows the distribution of elasticities of all Kimball specifications (Finite-Finite, Finite-Infinite and Klenow-Willis) estimated using both the DP and IV instruments. The distribution of BLP elasticities is also reported. Values are truncated at 25.

and using the two different identification strategies.[29] This result, in addition to the evidence on the similarity of the interquantile range values reported in Table 1, confirms that the heterogeneity in the price elasticities estimated under the Kimball specification bears a close resemblance to that under the BLP specification.[30] Moreover, it shows that the distribution of elasticities, estimated using both the DP and the IV approaches, is robust to the choice of different families of the Kimball functions (Finite-Finite, Finite-Infinite and Infinite-Infinite).

3.4 Inferred Quality and Product Characteristics

Using detailed data on the US automobile market allows us to examine whether our approach retrieves meaningful measures of quality.[31] We examine this question by quantifying the correlation between our inferred measures of quality and the product characteristics valued by consumers available in our dataset. We again compare the results of our DP approach for the CES specification to alternatives estimation strategies such as OLS and the standard IV approach using RER. We also explore the implications of accounting for heterogeneity in price elasticities for the inferred quality (compared to the standard CES case).

In the CES case, the inferred quality of each product i at time t is computed according Equation (24) in which we use the elasticity estimated using the DP approach and reported in Table 1. Similarly, inverting the Kimball demand, we infer the measure of product quality for the Kimball case using Equation (18).[32] We then study the correlation between the quality measure $\widehat{\varphi}_{it}$ (inferred using either CES or Kimball) and a subset of product characteristics tightly linked to product quality in this specific market, e.g., horsepower, space, miles-per-dollar and style:

$$\widehat{\varphi}_{it} = \beta \boldsymbol{x}_{it} + \eta_t + \gamma_i + \epsilon_{it}, \tag{29}$$

where $\boldsymbol{x}_{it}$ is the set of characteristics listed above. The correlation coefficients estimated from regression (29) are compared against the coefficients estimated from Equation (28)

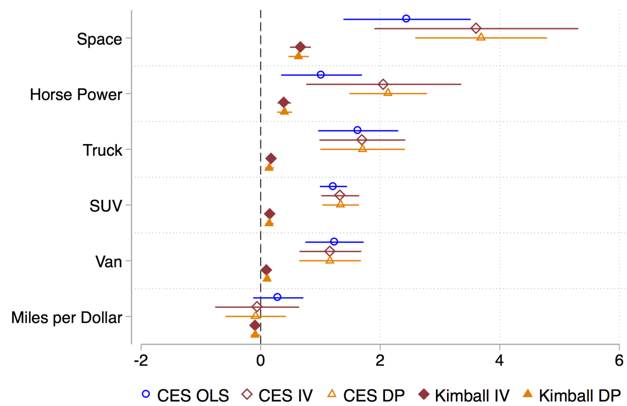
[29]See also Figure 8 in Appendix B for additional comparisons across Kimball specifications and identification strategies.

[30]Note that in the Kimball case, the heterogeneity in elasticities is entirely due to the heterogeneity in market shares. In contrast, the heterogeneity in the elasticities estimated by the BLP method may additionally stem from the heterogeneity in product characteristics as well.

[31]The availability of product characteristics in our dataset allows us to test directly our identification assumption. In Appendix B.2, we show that lagged prices are uncorrelated with current product characteristics after controlling for lagged product characteristics.

[32]See the discussion in Appendix A.3 for more details on inverting theKimball demand.

Figure 2: Correlation between Inferred Quality and Product Characteristics



Note: The figure reports the relationship between product characteristics and inferred quality. In the CES DP case, the inferred quality measure follows from Equation (24). For the Kimball specification, inferred quality is obtained inverting demand as in Appendix *A*.3. The coefficients referring to the DP approach (CES and Kimball) and the Kimball IV case are obtained from regression in Equation (29). We consider the following product characteristics: horse power, space, miles-per-dollar and style (suv, truck, van). The coefficients referring to the OLS and IV estimates of the CES specification are obtained from Equation (28), where product characteristics are used to proxy for quality. All regressions use the entire sample and includes time and product fixed effects. Standard errors are clustered at the producer level, the bands around the estimates show the 95% confidence intervals.

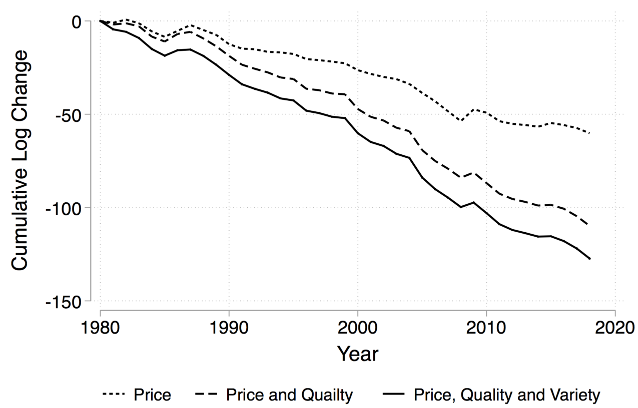
above.[33]

Figure 2 shows that the inferred quality estimated using DP and using the cost shock (RER) identification are related to product characteristics almost identically, in both the CES and the Kimball specifications. This is a direct consequence of the ability of the DP approach to correctly estimate price elasticities, as shown in the previous section. Notice that the correlation between inferred quality and product characteristics differs across model specifications. Even though the correlations exhibit the same qualitative patterns, the magnitude is stronger in the CES specification compared to Kimball. The quantitative difference across models suggests that accounting for heterogeneity in price elasticity has a first order role in quantifying the role of quality.

If we assume that the market structure is characterized by monopolistic competition, the markup charged for each vehicle-year is given by $\mu_{it} = \frac{1}{\sigma_{it}-1}$, where σ_{it} is the estimated price elasticity for vehicle i at time t. Given this measure of markups, we infer the marginal cost of each vehicle to be $mc_{it} = \frac{p_{it}}{1+\mu_{it}}$. The right panel of Figure 10 in Appendix B.3 shows that there is a strong positive relationship between a proxy of input cost, the weight of the vehicle multiplied by the price of steel, and our measure of inferred marginal cost, supporting the relevance of the latter. The left panel of Figure 10

[33]We re-estimate Equation (28) above using the same set of product characteristics and fixed effects as in regression (29).

Figure 3: Ideal Price Index for the US Auto Market



Note: The figure plots the ideal price index for the auto market and its decomposition into the unadjusted price, quality improvement and variety components. We use the estimates from the Finite-Finite Kimball specification estimated using the DP approach. The solid line represents the price index including all three components. The dashed and dotted lines represent the price and quality components together and the price component only, respectively. Prices are deflated using the CPI index from BLS. The measure of inferred quality is normalized such that the average change in quality of the set of continuing models that are not redesigned is zero.

shows that higher quality models have lower price elasticities and, thus, higher markups. The right panel of Figure 10 displays a positive relationship between inferred quality and the cost of production, in line with the findings of the prior literature on product quality (e.g., Verhoogen, 2008).[34]

3.5 The Evolution of Welfare in the Auto Market

We construct the ideal price index for the entire US auto market following Section 2.2 and analyze its evolution, quantifying the contribution of changes in unit price, quality, and the set of available models for consumers. We express the price changes relative to the CPI index constructed by the BLS. As before, quality is normalized such that the average quality change in the set of continuing models that are not redesigned between each two consecutive years is zero.[35]

In Figure 3 we plot the ideal Kimball price index for the US auto market over the 1980-2018 period, highligthing the role of theprice, quality, and variety channels. The price index on average declines by around 3.3% annually relative to the CPI over this period. Almost half of the annual decline (1.58%) can be attributed to the decline in unadjusted

[34]Consistent with this evidence, Figure 11 in Appendix B.3 shows that our measure of marginal costs is strongly correlated with the product characteristics consumers value (e.g. horsepower, space and miles-per-dollar).

[35]See footnote 27 for details on the normalization of quality.

unit price. Quality improvement contributes substantially to the overall fall in the price index, accounting for an additional 1.3% average annual decline. Figure 3 shows that the contribution of the availability of new models is marginal compared to the other two channels, accounting for a 0.46% annual drop in the aggregate price index.[36] Table 10 in Appendix B.3 compares the ideal price index for Kimball to the ideal price index for the CES case. The annual decline in the price index is 4% larger in the CES case because the contribution of quality improvements is largely overestimated (4.6% in the CES case compared to 1.3% in the Kimball case). In line with Proposition 2, the quantitative role of quality improvement for welfare changes deeply relies on the underlying preference structure.[37]

4 Consumer Gains from Imports

We now turn to the task of evaluating the impact of trade openness on the standards of living in the United States from 1989 to 2006, with a specific interest in the role of product quality. We first briefly outline a model of consumer demand for imports and define the corresponding price index building on the results of Section 2.2. We then present the results of estimating the US import demand with the DP approach and discuss the resulting measures of the change in the US import price index.

4.1 Import Demand and The Import Price Index

We assume that the preferences of the representative US consumer can be characterized by a nested utility function that aggregates imported varieties into a composite import good that is consumed together with a composite domestic good. The first tier of the nested structure is given by $Q_t = \mathcal{F}_1(q_{D,t}, q_{M,t})$ where $q_{D,t}$ is the composite domestically produced good, $q_{M,t}$ is the composite imported good defined below, and where $\mathcal{F}_1(\cdot,\cdot)$ is an homothetic aggregator function that defines the consumption aggregate Q_t. In the second tier, the composite imported good $q_{M,t}$ aggregates a vector of K sectoral imported goods $\boldsymbol{q}_{M,t} \equiv (q_{kt}) \in \mathbb{R}^K$ according to another homothetic aggregator $q_{M,t} = \mathcal{F}_2(\boldsymbol{q}_{M,t})$.

Finally, in the third tier, the composite imported good for each sector k is defined by aggregating all varieties i within that sector:

[36] Grieco et al. (2021) also attributes the bulk of the increase in consumer surplus in the auto industry to quality improvements, while a marginal role is played by the entry of new varieties.

[37] We can use our estimation results to explore the evolution of markups and marginal cost in the US auto market. Figure 12 in Appendix B.3 shows that markups (marginal cost) are increasing (decreasing) over the period 1980-2018, in line with previous work on this industry, Grieco et al. (2021).

$$\sum_{i \in V_{kt}} \mathcal{K}\left(e^{\varphi_{kit}} \frac{q_{kit}}{q_{kt}}; \varsigma_k\right) = 1 \tag{30}$$

where $\mathcal{K}(\cdot; \varsigma_k)$ is the Kimball aggregator for the varieties in sector k, q_{kit} and φ_{kit} stand for the consumption level and quality of variety i in sector k, and V_{kt} is the set of all imported varieties consumed in sector k. We follow the standard approach to identify varieties with the country of origin (Armington assumption). As for the Kimball function, we consider the standard CES aggregator and our Finite-Finite specification of the Kimball preferences in Equation (10).

Our goal is to measure the change in the relative price of imports, given by $\Delta \log p_{M,t} \equiv \log(p_{M,t}/p_{M,t-1})$. We take the price of the consumption compositve Q_t to be the numeraire, and express the prices of imported goods relative to the price index of the representative US consumer. Assuming that the number of sectors remains constant over time, we can approximate the change in the unit cost of the bundle of imported goods using the Törnqvist price index (Diewert, 1976, 1978; Jaravel and Lashkari, 2021):

$$\Delta \log p_{M,t} \approx \sum_k s^*_{kt,T} \, \Delta \log p_{kt}, \tag{31}$$

where we have defined $\Delta \log p_{k,t} \equiv \log(p_{k,t}/p_{k,t-1})$, and where the Törnqvist sectoral weight $s^*_{kt,T}$ is the average share of sector k is the total volume of import between periods $t-1$ and t, that is, $s^*_{kt,T} \equiv \frac{1}{2}(s_{kt-1} + s_{kt})$.

To compute the aggregate import price index from Equation (31), we need to compute change $\Delta \log p_{kt}$ in the logarithm of the unit cost for each sector k, relying on the results of Section 2.2. As we discuss below, we first estimate the Kimball demand system, separately for each sector, using the technique presented in Section 2.3, and then use Equation (12) to compute the price index and Proposition 1 to approximately decompose the change in the ideal price index for each sector into the change in unadjusted unit value, quality, and variety. We also estimate a CES demand and use Proposition 2 to examine the difference between the contribution of quality as inferred by the Kimball and the CES demand systems.

4.2 Data and Estimation

We use product-level data on US imports from 1989 to 2006 compiled by Feenstra et al. (2002). These data record US imports at the 10-digit level of the Harmonized System (henceforth HS10), reporting also the corresponding SITC classification. We define a good to be an HS10 category and we follow the standard approach to identify varieties with the country of origin, e.g., an exporter-HS10 pair. A variety's unit value is defined as the sum of the value, total duties, and transportation costs divided by the import quantity. To correctly evaluate the role of prices, we deflate import prices and expenditure using the official measure of CPI from the Bureau of Labor Statistics and express all variables in constant 1989 prices.[38] To minimize the effects of noise in the data, we trim the data as follow: we exclude all varieties that report a quantity of one unit or less than the 5th percentile within each HS10 product category; we remove varieties with annual unit value increase that fall below the 5th percentile or above the 95th percentile within each HS10 product category.

We estimate the CES elasticity of substitution across product varieties at the HS10 level, together with the 5, 4 and 3-digit SITC levels of aggregation (SITC5, SITC4 and SITC3, respectively).[39] We use our Dynamic Panel (DP) approach using the moment condition in Equation (26) with double lagged (log) prices and market shares as instruments. We compare our estimates against those found using the conventional Feenstra (1994) and Broda and Weinstein (2006) estimator (henceforth FBW) and as well as the more recent Limited Information Maximum Likelihood estimation approach (Soderbery, 2015, henceforth LIML). We next apply the DP approach to the Finite-Finite specification of the Kimball preferences at the SITC3 level.[40] We use the moment condition in Equation (23) with lagged log prices and quantities and their quadratic power as instruments.[41]

For the DP estimation, we use any continuously imported variety over the period from 1989 to 2006 within each product classification as the baseline product.[42] For measuring the price index, we create a basket of OECD countries as our baseline O for quality ($\frac{1}{|O|}\sum_{o\in O}\varphi_{ot} = 0$) within each product classification, assuming that the average quality of varieties imported from these countries are similar to those of domestic US producers, and that the latter is reflected in the US CPI. This allows us to express the quality of the varieties supplied by all other countries relative to this baseline.

[38]In Appendix C.4 we report the welfare calculations using the US producer's price index (PPI) as the price deflator. The main qualitative conclusions of our welfare analysis do not change.

[39]The SITC4 level allows us to map our data to the Rauch product classification (Rauch, 1999).

[40]For the Kimball preferences, we restrict our attention to the SITC3 level because, as more disaggregated levels are considered, the probability of not having a continuosuly imported variety to use as reference product decreases.

[41]In case the estimated values were not feasible with this set of instrument, we added the third power of both lagged log prices and quantities.

[42]In practice, this restricts the possibility to the major advanced economies and few other exporters.

4.3 Estimates of the Elasticitiy of Substitution

Elasticities under the CES Model Table 2 compares the price elasticities estimated by the different strategies across different product classifications. First, note that the magnitude of the estimated price elasticities falls as we estimate them across more aggregated varieties, as varieties become less substitutable at these more aggregated levels.[43] Comparing the magnitudes across different methods, we find that the elasticities estimated using DP are larger compared to those obtained using the FBW or LIML methods, in both mean and median terms, at all levels of aggregation. For instance, at the three-digit level, the mean elasticity for DP is 4.5, 50% greater than FBW, and almost three times larger than LIML. Similarly, the median elasticity for DP is 2.8, while the value is 2.3 and 1.2 for the conventional methods FBW and LIML, respectively. We can easily reject the hypothesis that the means and the medians are the same, suggesting that convential estimates suffer from a downward bias.[44] As we discussed in Section 2.3.2, the the FBW and LIML methods assume uncorrelated demand and supply shocks, which is likely to be violated when marginal cost depends on quality. The resulting positive correlation between demand and supply shocks should lead to a downward bias in the price elasticities estimated by the two conventional methods, consistent with the results in Table 2. As we will see in the following subsection, the bias in the estimates of the elasticity of substitution plays an important role in the predictions of these methods for the inferred quality gains.

Table 2: Comparison between DP, FBW and LIML

	HS 10			SITC 5			SITC 3		
	DP	BW	LIML	DP	BW	LIML	DP	BW	LIML
Mean	5.70	4.64	4.50	5.09	3.44	3.21	4.49	2.97	1.70
(SE)	(0.15)	(0.09)	(0.11)	(0.23)	(0.13)	(0.15)	(0.45)	(0.39)	(0.11)
Median	3.35	2.74	2.10	3.08	2.43	1.65	2.79	2.29	1.23
(SE)	(0.05)	(0.02)	(0.02)	(0.10)	(0.04)	(0.04)	(0.25)	(0.08)	(0.03)
T-statistics		7.89	8.08		6.40	6.91		2.56	6.06
Pearson χ^2 p-value		0.00	0.00		0.00	0.00		0.03	0.00
N	7283	7283	7283	1140	1140	1140	127	127	127

Note: Mean and median of the elasticities of substitution estimated with the DP, FBW and LIML methods for the HS10, SITC5 and SITC3 levels of aggregation. Only feasible estimates for common products are reported. Values above 130 are censored. Standard errors for each statistics are bootstrapped. For each level of aggregation, T-statistics refer to a t-test for differences in mean with respect to DP; p-values for Pearson difference in median tests with respect to DP.

Intuitively, we expect the magnitude of the price elasticities to be higher among more homogenous goods compared to more differentiated ones, since these homogenous goods

[43] Appendix C.1 provides a more extensive discussion of this result for the DP estimates.

[44] Figure 21 in Appendix C.4 shows the strong correlation among the estimates found by the three methods.

should be more substitutable (Broda and Weinstein, 2006). In Appendix C.1, we use the standard Rauch (1999) classification to distinguish products at the SITC4 level into three categories: commodities, referenced priced, and differentiated goods, and show that our estimated price elasticities are lower for more differentiated products. More interestingly, we also show that the downward bias in the FBW and LIML methods is stronger for more differentiated product categories, since quality should be more relevant for this type of products compared to more homogenous ones.

Elasticities under the Kimball Model We now turn our attention to the estimated price elasticities for the Kimball model and compare them to the corresponding CES estimates.[45] Table 3 compares different moments of the distribution of elasticities across varieties between Kimball and CES estimates.[46] We find larger estimates under the Kimball demand system, in terms of mean, median, and both lower and upper tails of the distribution. This result suggests that ignoring the heterogeneity in price elasticities across varieties leads to a bias in the estimated price elasticity at the variety level. Figure 4 orders all sectors from left to right based on the share-weighted mean elasticity under Kimball, reporting the estimated lower and upper limits of the Kimball specification, the expenditure share weighted Kimball elasticitiy, and the estimated CES elasticity for each SITC3. The solid black line shows that there is a strong positive correlation between the expenditure-share weighted mean Kimball elasticity and the corresponding CES elasticity.[47] However, the estimated lower and upper limits of the Finite-Finite specification show the existence of an extensive heterogeneity in the price elasticities across varieties within each sector, suggesting that the CES assumption can be a poor approximation for the degree of own-price elasticity for many individual varieties.[48]

In line with the results from the US auto market, Figure 16 in Appendix C.2 shows that

[45]Table 13 in Appendix C.2 reports summary statistics of the distribution of the estimated Finite-Finite Kimball parameters.

[46]Recall that for the Kimball specification, we can compute the elasticity for each variety at each moment in time while in the CES case we only compute a common value across time and varieties, within each SITC3. The moments for CES are computed assuming that each variety-time pair within the same sector has the same elasticity.

[47]The CES elasticities reported in Figure 4 are estimated using CES as the limiting case of the Kimball specification ($\sigma_o \equiv \sigma$). Figure 22 in Appendix C.4 shows that there is almost a perfect match between the estimates obtained using the limiting Kimball moment and the moment conditions in first-differences used for elasticities reported in Table 11.

[48]Figure 15 in Appendix C.2 illustrates the extent of the heterogeneity in elasticities for the Watches and Clocks sector (SITC3 number 884). The figure reports the entire set of Kimball elasticities, their expenditure-share weighted mean, and the CES estimate. Even if the expenditure-weighted mean Kimball elasticity is very close to the CES estimate (4.02 compared to 4.69), the Kimball prices elasticities range from 2 to 15 and decrease with market share.

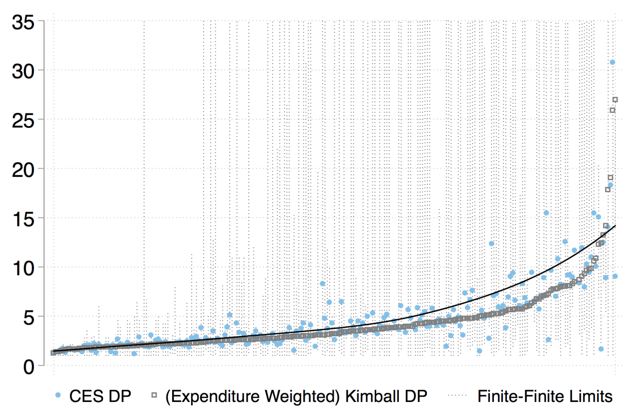
Table 3: Kimball Elasticities

	Kimball	CES
Mean	8.82	5.17
Median	4.66	3.87
Weighted Mean	6.62	7.18
p5	1.85	1.63
p95	27.0	10.2

Note: The table reports the mean, median, and both the 5th and 95th percentiles of the distribution of price elasticities for both the Kimball and CES specifications. For the Kimball specification, we can compute the elasticity for each variety at each moment in time while, in the CES case, each variety-time pair is associated with the corresponding sectoral CES elasticity.

varieties with higher inferred quality have higher expenditure shares and lower price elasticities. Consistent with these findings, Figure 17 in Appendix C.2 shows that the Kimball elasticity, Γ_{it}, is positively (inversely) related to the price elasticity (quality and expenditure share).

Figure 4: Comparison with CES Elasticities

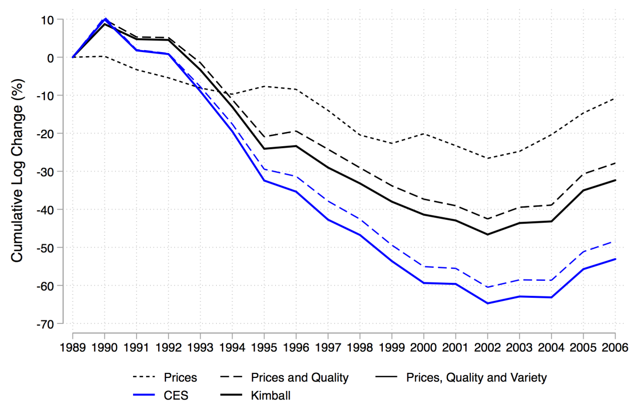


Note: In the figure we rank each SITC3 sector by the expenditure-share weighted mean Kimball price elasticity. For each sector, it display the estimated lower and upper limits of the Finite-Finite Kimball specification (dotted line), the expenditure-share weighted mean Kimball price elasticity (gray squares) and the corresponding CES estimate (blue circles). The upper limits are truncated at 35. The solid black line shows a fitted curve through the CES estimates.

4.4 The Evolution of the US Import Price Index

Figure 5 reports the cumulative change in the aggregate price of US imports relative to the CPI from Equation (31), where the changes in the sector-level Kimball price indices are approximated using the expression in Equation (14). The figure also provides a decomposition of the change in the aggregate index to the three sources of interest. Improved product quality constitutes the primary source of consumption gains from openness in the US, accounting for more than half of the total decline in relative import prices. The import price index declined by around 32% (1.80% annually) relative to the CPI over the 1989-2006 period.[49] A price index including only changes in unadjusted prices would find the cumulative decline in the aggregate import price index over the period to be around 11%. Figure 5 and Table 4 also show that the impact of new varieties is marginal compared to the role of quality improvement, accounting for a 4.5% cumulative (0.25% annually) drop in the aggregate import price index. Standard price indices would therefore largely underestimate the overall decline in import prices.[50]

Figure 5: Dynamics of US Import Price Index



Note: The figure plots the aggregate import price indices for both the CES and Kimball case and their decomposition into the price, quality and variety components, according Equations (14) and (15). Prices are deflated using the CPI index from BLS. The measure of inferred quality is normalized such that the average quality of the set of OECD varieties is zero. The solid lines represent the aggregate import price index including all three components. The dashed and dotted lines represent the price and quality components together and the price component only, respectively. Black (Blue) lines refer to the Kimball (CES) specification.

Using CES preferences instead of Kimball doubles the consumption gains arising from the product quality channel, leading to a sizable overestimation of the overall gains. The CES aggregate price index for imports shows a decline of around 53% (2.95% annually), 30% more than the Kimball case. The stark difference with respect to the Kimball aggregate price index arises mainly from thedifferent estimates of the role of quality upgrading. Whereas quality improvement reduces the CES aggregate import price by 37.5%, the corresponding contribution using Kimball is only 17%. Table 4 shows that under the CES model the impact of new varieties is still marginal but larger than that suggested by the Kimball specification. This confirms the quantitative importance of departing from the

[49]Figure 23 in Appendix C.4 shows that the year-to-year change in the price component of our aggregate import price index strongly resembles the Import Price Index constructed by the BLS.

[50]In Appendix C.4, Figure 24 and Table 16 show the welfare gains from trade and their decomposition when prices are deflated using the PPI.

constant elasticity assumption in the standard CES demand systems for evaluating the consumption gains from trade, and in particular the role of product quality.

Table 4: Welfare Gains from Trade

	Total		Decomposition				
			Price	Quality		Variety	
	Kimball	CES		Kimball	CES	Kimball	CES
Cumulative Change (%)	-32.3	-53.1	-10.8	-17.1	-37.5	-4.48	-4.76
Annual Change (%)	-1.80	-2.95	-0.60	-0.95	-2.09	-0.25	-0.26

Note: The table reports the cumulative and average annual change in the aggregate import price indices defined in Equations (14) and (15) and reported in Figure 5, and their decomposition. Prices are deflated using the CPI index from BLS. The measure of inferred quality is normalized such that the average quality of the set of OECD varieties is zero.

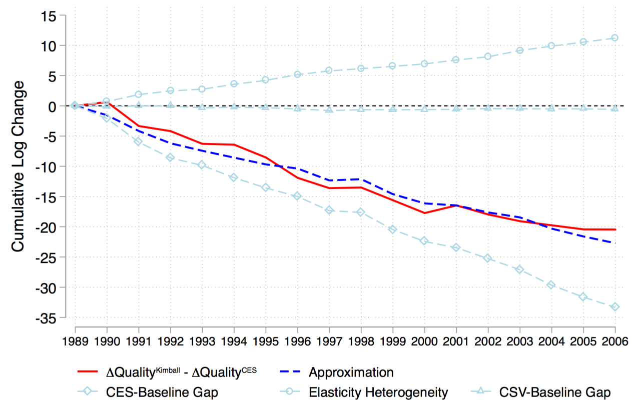
4.4.1 Bias in CES-inferred Quality

Proposition 2 provides a decomposition of the gap between what Kimball and CES demand systems predict about the contribution of quality change to the aggregate price index. This gap is the sum of three terms: the gap in the love-of-variety proxies inferred by the two demand systems(CES-Baseline Gap), the contribution of reallocations of expenditure across products (Elasticity Heterogeneity) and the heterogeneity in own-price elasticities and the love-of-variety proxies between the common set of varieties and the set of baseline products (CVS-Baseline Gap).

Figure 6 shows the cumulative gap between Kimaball and CES and its decomposition into the the three components based on Proposition 2. The contribution of the first term, the gap in thelove-of-variety estimates between CES and the baseline varieties under Kimball, is negative and explains more than 100% of the gap. Since the market share of OECD countries within the common set of varieties is falling over time, the key reason for the overestimation of the contribution of quality by CES is simply that its estimated elasticities suffer from a downward heterogeneity bias. The contribution of the second term, the reallocation within the common set of varieties, is positive, suggesting that there are reallocations toward varieties with low price elasticities within each sector over time. Finally, the last term, which is the gap in elasticities between the common set of varieties and the baseline varieties, appears fairly small. The dashed blue line shows the sum of all the three terms in the approximation, which is fairly close to the overall gap implied by the estimated Kimball and CES specifications (red line).

The left panel of Figure 18 in Appendix C.3 shows that if we use the expenditure-weighted mean Kimball elasticity for all varieties within each sector as the price elasticity

Figure 6: Quality Contribution: Kimball vs CES



Note: The figure plots the decomposition of the gap in the Torqvist-weighted mean quality change between the inferred quality using Kimball and that under CES. The solid red line represents the estimate Kimball-CES gap in aggregate quality change. The dashed blue line represents the approximation of the gap according Proposition 2. The approximation is the sum of three components: the gap in the love-of-variety proxies (CES-Baseline Gap, diamonds line), the contribution of reallocations of expenditure across products (Elasticity Heterogeneity, circles line) and the heterogeneity in own-price elasticities and the love-of-variety proxies between the common set varieties and the set of baseline products (CVS-Baseline Gap, triangles line).

of a CES demand system, the overestimation of the contribution of quality change falls to 7.3%. This result again highlights the fact that the heterogeneity bias in the estimated elasticities under the CES demand is the main driver of the larger contribution of quality change under CES demand.[51]

4.4.2 The Role of Variety

Although quantitatively less relevant than the role of quality upgrading, the contribution of variety in Proposition 2 also depends on the demand system used to evaluate it. Table 5 shows that the gains from varieties in the presence of variable elasticity demand are smaller because the adjusted contribution of the growth in the expenditure share of common varieties, $\frac{1-\bar{\Gamma}^*_{kt}}{\bar{\Gamma}^*_{kt}} \log\left(\Lambda^-_{kt}/\Lambda^+_{kt-1}\right)$, is smaller than in the CES case, $\frac{1}{\sigma_k - 1} \log\left(\Lambda^-_{kt}/\Lambda^+_{kt-1}\right)$. This occurs because the Kimball ratio $\frac{1-\bar{\Gamma}^*_{kt}}{\bar{\Gamma}^*_{kt}}$, which depends on the Kimball demand index of the common varieties set, is smaller than the CES elasticity ratio (see Figure 25 in Appendix C.4). Moreover, the growth in the Kimball demand index across all vari-

[51]Remember that when we compare two CES demand systems with different sets of elasticities across different sectors, the first term in Proposition 2 is the only driver of potential differences in inferred quality changes. The right panel of Figure 18 and Table 14 in Appendix C.3 shows that, for the CES case, using the LIML estimated elasticities instead of the DP ones largely overestimates the contribution of quality because the estimated LIML elasticities are smaller than the DP ones. The difference is much smaller if we use the FBW estimates, consistent with the fact that the FBW estimated elasticities are upward biased with respect to the LIML ones.

Table 5: Gains from Variety

	CES	Kimball	Decomposition Kimball	
			$\frac{1-\bar{\Gamma}^*_{kt}}{\bar{\Gamma}^*_{kt}} \log\left(\frac{\Lambda^-_{kt}}{\Lambda^+_{kt-1}}\right)$	$\log\left(\frac{\overline{\Gamma}_t}{\overline{\Gamma}_{t-1}}\right) - \log\left(\frac{\overline{\Gamma}^-_t}{\overline{\Gamma}^+_{t-1}}\right)$
Cumulative Contribution (%)	-4.74	-4.46	-4.64	0.18

The table reports the cumulative contribution of variety churn to the aggregate import price indices, as defined in Equations (14) and (15). For the Kimball specification, we report also the decomposition between the contribution of the growth in the expenditure share of common varieties (third column) and the gap in the growth of the harmonic mean of the Kimball elasticities across all and across common varieties (fourth column).

eties is stronger than that among the common varieties, that is, the term $\log\left(\overline{\Gamma}_t/\overline{\Gamma}_{t-1}\right) - \log\left(\overline{\Gamma}^-_t/\overline{\Gamma}^+_{t-1}\right)$ is positive, which further reduces the gains from varieties in the variable elasticity case.

4.5 Decomposing Quality Change across Exporters

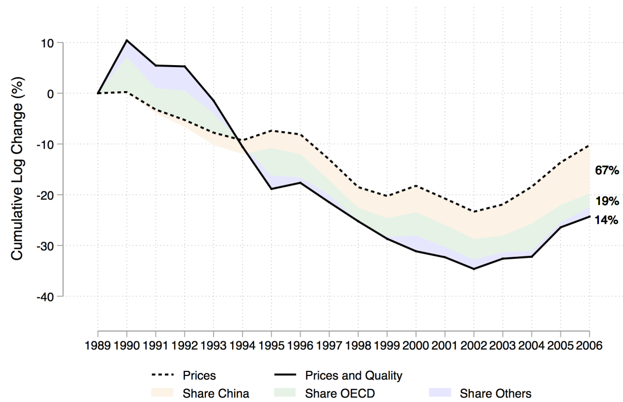
We now focus our attention on the main source of consumption gains, quality upgrading, and decomponse the aggregate quality change to the contributions of major exporter to the US, distinguishing China, the OECD economies, and all other exporters.

Figure 7 shows that about 70% of the total cumulative gains from quality can be attributed to quality improvements of Chinese varieties relative to the baseline , i.e. the average quality across OECD varieties.[52] The contribution of the OECD countries and all the other exporters to the overall quality improvement is about 20% and 14%, respectively.[53] Chinese products represent the largest source of quality improvements and, ultimately, gains from trade experienced by the US. This result is in line with the prior work documenting that the expansion of Chinese exports is not limited to the low-skill labor intensive and low-quality goods (Hsieh and Ossa, 2016). Figure 7 further shows that the quality upgrading accelerates after China's accession to the WTO. Nevertheless, the quality catch-up is already in progress in the 90s. This result is again consistent with the fact that the path of economic reforms in China goes further back in time to the late 70s (Brandt et al., 2017; Fan et al., 2015, 2017).

[52]Notice that the normalization used to evaluate quality does not imply that the contribution of quality changes of the OECD countries is zero. The contribution of quality change among OECD varieties is the Tornqvist weighted mean of variety-level quality change, while our baseline sets the unweighted mean quality among the OECD varieties to zero.

[53]Figure 26 in Appendix C.4 shows the same decomposition for the CES case. Chinese varieties still represent the major source of quality improvements, accounting for 46% of the aggregate quality improvement. OECD and other exporters' varieties account for the 28% and the 26% of the aggregate quality improvement, respectively. Departing from the constant elasticity assumption is important not only in evaluating the aggregate role of quality for the gains from trade, but also in decomposing its sources.

Figure 7: Decomposition of Quality across Countries



Note: The dashed line shows the price component of the aggregate import price index. The solid line shows the price component together with the quality component of the aggregate import price index. The quality contribution is computed using the inferred quality from the Kimball specification. The difference between these two lines quantifies the role of quality changes and is decomposed into the role of Chinese varieties (orange area), OECD varieties (green area) and all other varieties pooled together (purple area).

5 Conclusion

In this paper, we examined the role of quality improvements for the consumption gains from globalization in the context of the changes in the size and composition of US imports over the 1989-2006 period. We implemented a novel methodology to infer quality changes in a flexible demand model using only data on prices and market shares, and derived an approximate decomposition of the changes in the relative price of imports into the contribtuions of changes in prices, quality, and the variety in the set of available products. Moreover, we independently validated our approach in the context of the US auto market in which additional information on product chacteristics is available. Our baseline results suggest that, over the period from 1989 to 2006, quality improvements accounted for more than half of gains from trade in the US and 70% of these gains arise from the improvement in the quality of Chinese products. By ignoring the heterogeneity in price elasticities, the gains from quality are largely overestimated, indicating the importance of departing from the standard CES assumption in our accounting of the role of quality. Applying our novel methodology to other economies, as well as to firm-level data to include pro-competitive effects and their interaction with quality, are promising venues for future research.

References

Ackerberg, Daniel A, “Timing Assumptions and Efficiency: Empirical Evidence in a Production Function Context," 2016. 17

Adao, Rodrigo, Dina Pomeranz, Dave Donaldson, Rodrigo Adão, Paul Carrillo, Costinot Arnaud, Dave Donaldson, and Dina Pomeranz, "Imports, Exports, and Earnings Inequality: Measures of Exposure and Estimates of Incidence," *Quarterly Journal of Economics*, 2022. 5

Amiti, Mary, Oleg Itskhoki, and Jozef Konings, "International shocks, variable markups, and domestic prices," *The Review of Economic Studies*, 2019, *86* (6), 2356–2402. 6

Arkolakis, Costas, Arnaud Costinot, Dave Donaldson, and Andres Rodriguez-clare, "The elusive of pro-competitive effect of trade," 2017. 5

Autor, David H., David Dorn, and Gordon H. Hanson, "The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade," *Annual Review of Economics*, 2016, *8*, 205–240. 2

Baqaee, David and Emmanuel Farhi, "The Darwinian Returns to Scale," *National Bureau of Economic Research*, 2020. 9

Baqaee, David Rezza and Emmanuel Farhi, "Productivity and misallocation in general equilibrium," *The Quarterly Journal of Economics*, 2020, *135* (1), 105–163. 6

Berlingieri, Giuseppe, Holger Breinlich, and Swati Dhingra, "The impact of trade agreements on consumer welfareâEvidence from the EU common external trade policy," *Journal of the European Economic Association*, 2018, *16* (6), 1881–1928. 4, 5

Berry, Steven, James Levinsohn, and Ariel Pakes, "Automobile prices in market equilibrium," *Econometrica: Journal of the Econometric Society*, 1995, pp. 841–890. 3, 18, 19, 20

Berry, Steven T, "Estimating Discrete-Choice Models of Product Differentiation Authors," *The RAND Journal of Economics*, 1994, *25* (2), 242–262. 3, 18, 19, 20

_, Amit Gandhi, and Philip A Haile, "Connected Substitutes and Invertibility of Demand," *Econometrica*, 2013, *81* (5), 2087–2111. 49

Borusyak, Kirill and Xavier Jaravel, "The Distributional Effects of Trade: Theory and Evidence from the United States," 2018. 5

Boskin, Michael J., Ellen R. Dulberger, Robert J. Gordon, Zvi Griliches, and Dale W. Jorgenson, "Consumer Prices, the Consumer Price Index, and the Cost of Living," *Journal of Economic Perspectives*, 1998, *12* (1), 3–26. 2

Brandt, Loren, Johannes Van Biesebroeck, Luhang Wang, and Yifan Zhang, "WTO accession and performance of Chinese manufacturing firms," *American Economic Review*, 2017, *107* (9), 2784–2820. 5, 35

Broda, Christian and David E Weinstein, "Globalization and the Gains from Variety," *The Quarterly journal of economics*, 2006, *121* (2), 541–585. 2, 3, 12, 28, 30

Conlon, Christopher and Jeff Gortmaker, "Best practices for differentiated products demand estimation with pyblp," *The RAND Journal of Economics*, 2020, *51* (4), 1108–1161. 20

Costinot, Arnaud and Andrés Rodríguez-Clare, "Trade Theory with Numbers: Quantifying the Consequences of Globalization," in "Handbook of International Economics," Vol. 4, Elsevier B.V., 2015, pp. 197–261. 5

Crozet, Matthieu, Keith Head, and Thierry Mayer, "Quality sorting and trade: Firm-level evidence for French wine," *The Review of Economic Studies*, 2012, *79* (2), 609–644. 2

Dhingra, Swati and John Morrow, "Monopolistic competition and optimum product diversity under firm heterogeneity," *Journal of Political Economy*, 2019, *127* (1), 196–232. 9

Diewert, W Erwin, "Exact and superlative index numbers," *Journal of Econometrics*, 1976, *4* (2), 115–145. 27

_ , "Superlative Index Numbers and Consistency in Aggregation," *Econometrica*, 1978, *46* (4), 883–900. 27

Dingel, Jonathan I, "The determinants of quality specialization," *The Review of Economic Studies*, 2017, *84* (4), 1551–1582. 2

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu, "Competition, markups, and the gains from international trade," *American Economic Review*, 2015, *105* (10), 3183–3221. 6

Fajgelbaum, Pablo, Gene M Grossman, and Elhanan Helpman, "Income distribution, product quality, and international trade," *Journal of political Economy*, 2011, *119* (4), 721–765. 2

Fan, Haichao, Yalo Amber Li, Sichuang Xu, and Stephen R Yeaple, "Quality, variable markups, and welfare: a quantitative general equilibrium analysis of export prices," 2017. 35

— **, Yao Amber Li, and Stephen R Yeaple**, "Trade liberalization, quality, and export prices," *Review of Economics and Statistics*, 2015, *97* (5), 1033–1051. 5, 35

Feenstra, Robert C, "New product varieties and the measurement of international prices," *The American Economic Review*, 1994, pp. 157–177. 2, 3, 4, 12, 18, 28, 50, 51, 52

— , *Product variety and the gains from international trade*, Cambridge, MA: MIT Press, 2010. 51

— **and David E Weinstein**, "Globalization, markups, and US welfare," *Journal of Political Economy*, 2017, *125* (4), 1040–1074. 5, 6

— **and John Romalis**, "International prices and endogenous quality," *The Quarterly Journal of Economics*, 2014, *129* (2), 477–527. 5

— **,** — **, and Peter K Schott**, "US imports, exports, and tariff data, 1989-2001," 2002. 27

Flam, Harry and Elhanan Helpman, "Vertical product differentiation and advertising," *American Economic Review*, 1987, *77* (5), 810–822. 2

Gábor-Tóth, Eniko and Philip Vermeulen, "The Relative Importance of Taste Shocks and Price Movements in the Variation of Cost-of-Living: Evidence From Scanner Data," 2018. 6

Goldberg, Pinelopi Koujianou and Frank Verboven, "The evolution of price dispersion in the European car market," *The Review of Economic Studies*, 2001, *68* (4), 811–848. 18

Gordon, Robert J and Zvi Griliches, "Quality change and new products," *The American Economic Review*, 1997, *87* (2), 84–88. 2

Grennan, Matthew, "Price discrimination and bargaining: Empirical evidence from medical devices," *American Economic Review*, 2013, *103* (1), 145–177. 3

Grieco, Paul LE, Charles Murry, and Ali Yurukoglu, "The evolution of market power in the US auto industry," Technical Report, National Bureau of Economic Research 2021. 6, 18, 19, 20, 26

Hallak, Juan Carlos, "Product quality and the direction of trade," *Journal of International Economics*, 2006, *68* (1), 238–265. 2

— **and Peter K Schott**, "Estimating cross-country differences in product quality," *The Quarterly journal of economics*, 2011, *126* (1), 417–474. 3, 5

Hsieh, Chang-Tai and Ralph Ossa, "A global view of productivity growth in China," *Journal of international Economics*, 2016, *102*, 209–224. 5, 35

— **, Nicholas Li, Ralph Ossa, and Mu-Jeung Yang**, "Accounting for the new gains from trade liberalization," *Journal of International Economics*, 2020, *127*, 103370. 4, 5

Hummels, David and Peter J Klenow, "The variety and quality of a nation's exports," *American economic review*, 2005, *95* (3), 704–723. 2, 5

Jaravel, Xavier, "Inflation Inequality: Measurement, Causes, and Policy Implications," *Annual Review of Economics*, 2021, *13*, 599–629. 5

— **and Danial Lashkari**, "Nonparametric Measurement of Long-Run Growth in Consumer Welfare," 2021. 12, 27

— **and Erick Sager**, "What Are the Price Effects of Trade? Evidence From the U.S. and Implications for Quantitative Trade Models," 2018. 5

Khandelwal, Amit, "The long and short (of) quality ladders," *The Review of Economic Studies*, 2010, *77* (4), 1450–1476. 3, 5, 7

Kimball, Miles S, "The quantitative analytics of the basic neomonetarist model," 1995. 3, 7, 49

Klenow, Peter J and Jonathan L Willis, "Real Rigidities and Nominal Price Changes," 2006. 9

Leamer, Edward E, "Is it a Demand Curve, Or is It A Supply Curve? Partial Identification through Inequality Constraints," *Review of Economics and Statistics*, 1981, *63* (3), 319–327. 50, 51, 52

Lee, Robin S, "Vertical integration and exclusivity in platform and two-sided markets," *American Economic Review*, 2013, *103* (7), 2960–3000. 3

Linder, Staffan B, *An Essay on Trade and Transformation*, Uppsala: Almqvist & Wiksells, 1961. 2

Martin, Julien and Isabelle Mejean, "Low-wage country competition and the quality content of high-wage country exports," *Journal of International Economics*, 2014, *93* (1), 140–152. 5

Matsuyama, Kiminori and Philip Ushchev, "Beyond CES: Three Alternative Classes of Flexible Homothetic Demand Systems," 2017. 49, 50

Rauch, James E, "Networks versus markets in international trade," *Journal of international Economics*, 1999, *48* (1), 7–35. 28, 30, 60, 61

Redding, Stephen J and David E Weinstein, "Measuring aggregate price indices with taste shocks: Theory and evidence for ces preferences," *The Quarterly Journal of Economics*, 2020, *135* (1), 503–560. 3, 4, 6, 7, 12

Schott, Peter K., "Across-Product Versus Within-Product Specialization in International Trade," *The Quarterly Journal of Economics*, 2004, *119* (2), 647–678. 2

Schott, Peter K, "Across-product versus within-product specialization in international trade," *The Quarterly Journal of Economics*, 2004, *119* (2), 647–678. 2, 5

_, "The relative sophistication of Chinese exports," *Economic policy*, 2008, *23* (53), 6–49. 5

Shu, P and C Steinwender, "The impact of trade liberalization on firm productivity and innovation. Innovation Policy and the Economy, Vol. 19," 2019. 5

Soderbery, Anson, "Estimating import supply and demand elasticities: Analysis and implications," *Journal of International Economics*, 2015, *96* (1), 1–17. 28, 51

Sweeting, Andrew, "Dynamic Product Positioning in Differentiated Product Markets: The Effect of Fees for Musical Performance Rights on the Commercial Radio Industry," *Econometrica*, 2013, *81* (5), 1763–1803. 3

Ueda, Kozo, Kota Watanabe, and Tsutomu Watanabe, "Product Turnover and the Cost-of-Living Index: Quality versus Fashion Effects," *American Economic Journal: Macroeconomics*, 2019, *11* (2), 310–347. 6

Verhoogen, Eric A, "Trade, quality upgrading, and wage inequality in the Mexican manufacturing sector," *The Quarterly Journal of Economics*, 2008, *123* (2), 489–530. 2, 25

Wang, Olivier and Iván Werning, "Dynamic oligopoly and price stickiness," Technical Report, National Bureau of Economic Research 2020. 6

A Proofs and Derivations

A.1 Proofs of Propositions

Proof for Proposition 1. Let us first compute the growth in the value of the Kimball sum $\sum_{i\in V_t^*} \mathcal{K}\left(\widetilde{q}_{it}\right)$ when limited to the set of common varieties between the two consecutive periods:

$$
\begin{aligned}
\log\left(\frac{\sum_{i\in V_t^*} \mathcal{K}\left(\widetilde{q}_{it}\right)}{\sum_{i\in V_t^*} \mathcal{K}\left(\widetilde{q}_{it-1}\right)}\right) &= \log\left(\frac{\left(\frac{\sum_{i\in V_t^*} \mathcal{K}(\widetilde{q}_{it})}{\sum_{i\in V_t^*} \widetilde{q}_{it}\mathcal{K}'(\widetilde{q}_{it})}\right)}{\left(\frac{\sum_{i\in V_t^*} \mathcal{K}(\widetilde{q}_{it-1})}{\sum_{i\in V_t^*} \widetilde{q}_{it-1}\mathcal{K}'(\widetilde{q}_{it-1})}\right)}\right) + \log\left(\frac{\sum_{i\in V_t^*} \widetilde{q}_{it}\mathcal{K}'\left(\widetilde{q}_{it}\right)}{\sum_{i\in V_t^*} \widetilde{q}_{it-1}\mathcal{K}'\left(\widetilde{q}_{it-1}\right)}\right), \\
&= -\log\left(\frac{\overline{\Gamma}_t^-}{\overline{\Gamma}_{t-1}^+}\right) + \log\left(\frac{\sum_{i\in V_t^*} \widetilde{q}_{it}\mathcal{K}'\left(\widetilde{q}_{it}\right)}{\sum_{i\in V_t^*} \widetilde{q}_{it-1}\mathcal{K}'\left(\widetilde{q}_{it-1}\right)}\right), \\
&= -\log\left(\frac{\overline{\Gamma}_t^-}{\overline{\Gamma}_{t-1}^+}\right) + \log\left(\frac{\left(\frac{\sum_{i\in V_t^*} \widetilde{q}_{it}\mathcal{K}'(\widetilde{q}_{it})}{\sum_{i\in V_t} \widetilde{q}_{it}\mathcal{K}'(\widetilde{q}_{it})}\right)}{\left(\frac{\sum_{i\in V_t^*} \widetilde{q}_{it-1}\mathcal{K}'(\widetilde{q}_{it-1})}{\sum_{i\in V_t} \widetilde{q}_{it-1}\mathcal{K}'(\widetilde{q}_{it-1})}\right)}\right) \\
&\qquad + \log\left(\frac{\sum_{i\in V_t} \widetilde{q}_{it}\mathcal{K}'\left(\widetilde{q}_{it}\right)}{\sum_{i\in V_t} \widetilde{q}_{it-1}\mathcal{K}'\left(\widetilde{q}_{it-1}\right)}\right), \\
&= -\log\left(\frac{\overline{\Gamma}_t^-}{\overline{\Gamma}_{t-1}^+}\right) + \log\left(\frac{\Lambda_t^-}{\Lambda_{t-1}^+}\right) + \log\left(\frac{\overline{\Gamma}_t}{\overline{\Gamma}_{t-1}}\right),
\end{aligned}
\tag{32}
$$

where in the second equality, we have used Equation (39) and definitions (13), and in the last equality, we have used definition (11) and the fact that $s_{it} \propto \widetilde{Q}_{it}\mathcal{K}'\left(\widetilde{q}_{it}\right)$. Henceforth, we will refer to the three terms in Equation as $-\Delta\gamma_t^*$, $\Delta\lambda_t$, and $\Delta\gamma_t$, respectively.

Using Lemma 1 below, we can approximate the left hand side of the above equation to the second order of approximation in $\Delta\log\widetilde{q}_{it}$ as:

$$
\begin{aligned}
\log\left(\frac{\sum_{i\in V_t^*} \mathcal{K}\left(\widetilde{q}_{it}\right)}{\sum_{i\in V_t^*} \mathcal{K}\left(\widetilde{q}_{it-1}\right)}\right) &\approx \frac{1}{2}\sum_{i\in V_t^*}\left(\frac{\widetilde{q}_{it-1}\mathcal{K}'\left(\widetilde{q}_{it-1}\right)}{\sum_{i\in V_t^*} \mathcal{K}\left(\widetilde{q}_{it-1}\right)} + \frac{\widetilde{q}_{it}\mathcal{K}'\left(\widetilde{q}_{it}\right)}{\sum_{i\in V_t^*} \mathcal{K}\left(\widetilde{q}_{it}\right)}\right)\Delta\log\widetilde{q}_{it}, \\
&= \frac{1}{2}\sum_{i\in V_t^*}\left(S_{it-1}^+ \cdot \overline{\Gamma}_{t-1}^+ + S_{it}^- \cdot \overline{\Gamma}_t^-\right)\Delta\log\widetilde{q}_{it},
\end{aligned}
\tag{33}
$$

where in the second equality, we have used Equations (39) and (4).

We next equate Equations (32) and (33), and simplify the expressions to find:

$$
\begin{aligned}
\Delta\lambda_t + \Delta\gamma_t - \Delta\gamma_t^* &\approx \frac{1}{2}\sum_{i\in V_t^*}\left(s_{it-1}^{+}\cdot\overline{\Gamma}_{t-1}^{+} + s_{it}^{-}\cdot\overline{\Gamma}_t^{-}\right)\Delta\log\left(e^{\varphi_{it}}\frac{q_{it}}{q_t}\right),\\
&= \frac{1}{2}\sum_{i\in V_t^*}\left(s_{it-1}^{+}\cdot\overline{\Gamma}_{t-1}^{+} + s_{it}^{-}\cdot\overline{\Gamma}_t^{-}\right)\Delta\log\left(e^{\varphi_{it}}\frac{p_{it}q_{it}/e_t^*}{p_{it}e_t/e_t^*}p_t\right),\\
&= \frac{1}{2}\sum_{i\in V_t^*}\left(s_{it-1}^{+}\cdot\overline{\Gamma}_{t-1}^{+} + s_{it}^{-}\cdot\overline{\Gamma}_t^{-}\right)\left(\Delta\log s_{it}^* - \Delta\log p_{it} + \Delta\varphi_{it} + \Delta\lambda_t + \Delta\log p_t\right),
\end{aligned}
$$

where in the second equality, we have let e_t and e_t^* stand for the expenditure across all varieties and common varieties, respectively, and in the last equality, we have defined $\Delta\log s_{it}^* \equiv \log(s_{it}^-/s_{it-1}^+)$ and $\Delta\lambda_t \equiv \log\left(\frac{\Lambda_t^-}{\Lambda_{t-1}^+}\right)$. Letting $\overline{\Gamma}_t^* \equiv \frac{1}{2}(\overline{\Gamma}_{t-1}^+ + \overline{\Gamma}_t^-)$, we can write the approximations $\overline{\Gamma}_{t-1}^+ \approx \overline{\Gamma}_t^*\left(1-\frac{1}{2}\Delta\gamma_t^*\right)$ and $\overline{\Gamma}_t^- \approx \overline{\Gamma}_t^*\left(1+\frac{1}{2}\Delta\gamma_t^*\right)$ where $\Delta\gamma_t^* \equiv \log\left(\overline{\Gamma}_t^-/\overline{\Gamma}_{t-1}^+\right)$. Substituting in the equation above, and a bit of algebra leads to:

$$
\begin{aligned}
\Delta\log p_t \approx \frac{1}{1+\Delta\gamma_t^*\left\langle\Delta\log s_{it}^*\right\rangle_T}\Bigg\{&\left(\frac{1-\Delta\gamma_t^*\left\langle\Delta\log s_{it}^*\right\rangle_T\overline{\Gamma}_t^*}{\overline{\Gamma}_t^*}\right)\Delta\lambda_t + \frac{\Delta\gamma_t - \Delta\gamma_t^*}{\overline{\Gamma}_t^*}\\
&+\langle\Delta\log p_{it}^*\rangle_T + \Delta\gamma_t^*\langle\Delta\log s_{it}^*\Delta\log p_{it}^*\rangle_T - \langle\Delta\varphi_{it}^*\rangle_T - \Delta\gamma_t^*\langle\Delta\varphi_{it}^*\Delta\log s_{it}^*\rangle_T\\
&-\langle\Delta\log s_{it}^*\rangle_T - \Delta\gamma_t^*\left\langle(\Delta\log s_{it}^*)^2\right\rangle_T\Bigg\},
\end{aligned}
$$

where $\langle\cdot\rangle_T$ denotes the mean across common varieties using the Törnqvist weights $s_{it,T}^*$. Noting that $\left\langle\Delta\log s_{it}^*\right\rangle_T$ is zero to the second order of approximation, we can drop terms of higher than second order to reach Equation (14). □

Proof of Proposition 2. Using the same notation as that of the proof of Proposition 1 above. For the Kimball specification, let us approximate a small change in Equation (35):

$$
\begin{aligned}
\Delta\log s_{it} = \Delta\log s_{it}^* + \Delta\lambda_t &\approx -\left(\sigma_{it}-1\right)\left(\Delta\log p_{it} - \Delta\varphi_{it} - \Delta\log p_t + \Delta\overline{\gamma}_t\right) - \Delta\overline{\gamma}_t,\\
&= -\left(\sigma_{it}-1\right)\left(\Delta\log p_{it} - \Delta\varphi_{it} - \Delta\log p_t\right) - \sigma_{it}\Delta\overline{\gamma}_t
\end{aligned}
$$

where we have used $\Delta\log p_t = \Delta\log h_t + \Delta\overline{\gamma}_t$ and σ_{it} the own-price elasticity given by Equation (6). This allows us to write:

$$
\Delta\log p_t \approx \Delta\log p_{it} - \Delta\varphi_{it} + \frac{1}{\sigma_i - 1}\Delta s_{it}^* + \frac{1}{\sigma_i-1}\Delta\lambda_t + \frac{\sigma_i}{\sigma_i-1}\Delta\overline{\gamma}_t.
$$

Using the normalization $\sum_{o\in O}\varphi_{ot}\equiv 0$, we find:

$$\Delta\log p_t \approx \langle\Delta\log p_{ot}\rangle + \left\langle \frac{1}{\sigma_{ot}-1}\Delta\log s^*_{ot}\right\rangle + \left\langle\frac{1}{\sigma_o-1}\right\rangle(\Delta\lambda_t+\Delta\overline{\gamma}_t)+\Delta\overline{\gamma}_t,$$

where we have defines $\langle x_{ot}\rangle \equiv \frac{1}{|O|}\sum_{o\in O}x_{ot}$ for any variable x.

Next, we compute the quality change under Kimball preferences:

$$\begin{aligned}\Delta\varphi_{it} &\approx \Delta\log p_{it} + \frac{1}{\sigma_{it}-1}\Delta\log s^*_{it} + \frac{1}{\sigma_{it}-1}\Delta\lambda_t + \frac{\sigma_{it}}{\sigma_{it}-1}\Delta\overline{\gamma}_t - \Delta\log p_t,\\ &\approx \Delta\log p_{it} - \langle\Delta\log p_{ot}\rangle + \frac{1}{\sigma_{it}-1}\Delta s^*_{it} - \left\langle\frac{1}{\sigma_{ot}-1}\Delta\log s^*_{ot}\right\rangle\\ &\quad+\left(\frac{1}{\sigma_{it}-1}-\left\langle\frac{1}{\sigma_{ot}-1}\right\rangle\right)(\Delta\lambda_t+\Delta\overline{\gamma}_t).\end{aligned}$$

If we instead assume CES, we simply find:

$$\Delta\varphi^{ces}_{it} = \log p_{it} - \langle\Delta\log p_{ot}\rangle + \frac{1}{\sigma-1}\left(\Delta\log s^*_{it} - \langle\Delta\log s^*_{ot}\rangle\right).$$

This leads to the following gap in quality inferred under Kimball and CES:

$$\begin{aligned}\Delta\varphi_{it}-\Delta\varphi^{ces}_{it} \approx&\left(\frac{1}{\sigma_{it}-1}-\frac{1}{\sigma-1}\right)\Delta\log s^*_{it} - \left\langle\left(\frac{1}{\sigma_{ot}-1}-\frac{1}{\sigma-1}\right)\Delta\log s^*_{ot}\right\rangle\\ &+\left(\frac{1}{\sigma_{it}-1}-\left\langle\frac{1}{\sigma_{ot}-1}\right\rangle\right)(\Delta\lambda_t+\Delta\overline{\gamma}_t).\end{aligned}$$

Noting again that $\sum_{i\in V^*_t} s^*_{it,T}\Delta\log s^*_{it}\approx 0$ to the second order of approximation, Equation (17) follows. □

Lemma 1. *Consider a function $f(\boldsymbol{x})$ defined in the space of $\boldsymbol{x}\in\mathbb{R}^I$. To the second order of approximation, we have:*

$$f(\boldsymbol{y})-f(\boldsymbol{x}) = \frac{1}{2}\sum_{i=1}^{I}\left[\frac{\partial f(\boldsymbol{y})}{\partial y_i}+\frac{\partial f(\boldsymbol{x})}{\partial x_i}\right](y_i-x_i).$$

Proof. Using Taylor's expansion, up to the second order in $\boldsymbol{y}-\boldsymbol{x}$, we have:

$$\begin{aligned}f(\boldsymbol{y}) &= f(\boldsymbol{x}) + \sum_{i=1}^{I}\frac{\partial f(\boldsymbol{x})}{\partial x_i}(y_i-x_i) + \frac{1}{2}\sum_{i,j=1}^{I}\frac{\partial^2 f(\boldsymbol{x})}{\partial x_i\partial x_j}(y_i-x_i)(y_j-x_j),\\ f(\boldsymbol{x}) &= f(\boldsymbol{y}) + \sum_{i=1}^{I}\frac{\partial f(\boldsymbol{y})}{\partial x_i}(x_i-y_i) + \frac{1}{2}\sum_{i,j=1}^{I}\frac{\partial^2 f(\boldsymbol{y})}{\partial x_i\partial x_j}(y_i-x_i)(y_j-x_j).\end{aligned}$$

Together, the two equations imply:

$$f(\boldsymbol{y}) = f(\boldsymbol{x}) + \frac{1}{2}\sum_{i=1}^{I}\left[\frac{\partial f(\boldsymbol{y})}{\partial y_i} + \frac{\partial f(\boldsymbol{x})}{\partial x_i}\right](y_i - x_i) + \frac{1}{4}\sum_{i,j=1}^{I}\left[\frac{\partial^2 f(\boldsymbol{x})}{\partial x_i \partial x_j} - \frac{\partial^2 f(\boldsymbol{y})}{\partial x_i \partial x_j}\right](y_i - x_i)(y_j - x_j).$$

This gives us the desired result since:

$$\frac{\partial^2 f(\boldsymbol{y})}{\partial x_i \partial x_j} - \frac{\partial^2 f(\boldsymbol{x})}{\partial x_i \partial x_j} = \sum_k \frac{\partial^3 f(\boldsymbol{x})}{\partial x_k \partial x_i \partial x_j}(y_k - x_k).$$

$\square$

A.2 Derivations for Kimball Specifications

Below, we derive the Kimball functions corresponding to each of the three cases discussed in Section 2.1. We have that $\mathcal{E}(\widetilde{q}) \equiv -d\log\mathcal{K}'(\widetilde{q})/d\log\widetilde{q}$. This allows us to integrate the function $\mathcal{E}(\cdot)$ twice to arrive at $\mathcal{K}(\cdot)$.

Klenow-Willis In this case, we have:

$$\begin{aligned}\psi(\log\widetilde{q}) \equiv \log\mathcal{K}'(\widetilde{q}) &= \xi - \frac{1}{\sigma}\int_{-\infty}^{\log\widetilde{q}} e^{\theta v} dv, \\ &= \xi - \frac{1}{\sigma\theta}\widetilde{q}^{\theta},\end{aligned}$$

for any constant ξ. Integrating this expression again, we find:

$$\begin{aligned}\mathcal{K}(\widetilde{q}) &= -e^{\xi}\int_{\log\widetilde{q}}^{\infty} e^{-v^{\theta}/\sigma\theta} dv, \\ &= e^{\xi}(\sigma\theta)^{\frac{1}{\theta}}\frac{1}{\theta}\Gamma\left(\frac{1}{\theta}, \frac{1}{\sigma\theta}\widetilde{q}^{\theta}\right),\end{aligned}$$

where $\Gamma(\cdot,\cdot)$ is the incomplete Gamma function.

Finite-Infinite Limits (FIL) In this case, we have:

$$\begin{aligned}\psi(\log\widetilde{q}) \equiv \log\mathcal{K}'(\widetilde{q}) &= \xi - \int_{-\infty}^{\log\widetilde{q}} \frac{dv}{\sigma + (\sigma_o - \sigma)e^{-\theta v}}, \\ &= -\frac{1}{\sigma}\log\widetilde{q} + \xi - \frac{1}{\sigma\theta}\log\left(\frac{\sigma}{\sigma_o - \sigma} + \widetilde{q}^{-\theta}\right).\end{aligned}$$

Next, we integrate to find the expression for $\mathcal{K}(\cdot)$:

$$\begin{aligned}\mathcal{K}(\widetilde{q}) &= e^{\xi}\int_0^{\log\widetilde{q}}\left(\frac{\sigma v^{\theta}+\sigma_o-\sigma}{\sigma_o-\sigma}\right)^{-\frac{1}{\sigma\theta}}dv,\\ &= e^{\xi}\,\widetilde{q}\cdot{}_2F_1\left(\frac{1}{\theta},\frac{1}{\sigma\theta};1+\frac{1}{\theta};-\frac{\sigma}{\sigma_o-\sigma}\widetilde{q}^{\theta}\right),\end{aligned}$$

where ${}_2F_1$ is the hypergeometric function. The functional form above implies the following expression for log demand:

$$\begin{aligned}d(\log\widetilde{p}) &\equiv \psi^{-1}(\log\widetilde{p}),\\ &= \frac{1}{\theta}\log\left[\frac{\sigma_o-\sigma}{\sigma}\left(e^{\theta\sigma(\xi-\log\widetilde{p})}-1\right)\right].\end{aligned}$$

In this case, there exists a finite chocke price for any product, above which demand drops to zero.

Finite-Finite Limits (FFL) In this case, we have:

$$\begin{aligned}\psi(\log\widetilde{q}) \equiv \log\mathcal{K}'(\widetilde{q}) &= \xi-\int_{-\infty}^{\log\widetilde{q}}\left[\frac{1}{\sigma_o}+\left(\frac{1}{\sigma}-\frac{1}{\sigma_o}\right)\frac{e^{\theta_o}e^{\theta v}}{1+e^{\theta_o}e^{\theta v}}\right]dv,\\ &= \xi-\frac{1}{\sigma_o}\log\widetilde{q}-\left(\frac{1}{\sigma}-\frac{1}{\sigma_o}\right)\frac{1}{\theta}\log\left(1+e^{\theta_o}\widetilde{q}^{\theta}\right).\end{aligned}$$

Finally, we integrate to find the expression for $\mathcal{K}(\cdot)$:

$$\begin{aligned}\mathcal{K}(\widetilde{q}) &= e^{\xi}\int_0^{\widetilde{q}}v^{-\frac{1}{\sigma_o}}\left(1+e^{\theta_o}v^{\theta}\right)^{-\left(\frac{1}{\sigma}-\frac{1}{\sigma_o}\right)\frac{1}{\theta}}dv,\\ &= e^{\xi}\frac{\sigma_o}{\sigma_o-1}\widetilde{q}^{1-\frac{1}{\sigma_o}}\cdot{}_2F_1\left(\left(1-\frac{1}{\sigma_o}\right)\frac{1}{\theta},\left(\frac{1}{\sigma}-\frac{1}{\sigma_o}\right)\frac{1}{\theta};1+\left(\frac{1}{\sigma_o}+1\right)\frac{1}{\theta};-e^{\theta_o}\widetilde{q}^{\theta}\right),\end{aligned}$$

where ${}_2F_1$ is the hypergeometric function.

A.3 Kimball Demand Inversion

We implement the demand inversion through the dual problem (4). Here, we consider a slightly more general case for the specification of the Kimball function $\mathcal{K}(\cdot)$ that allows for $\mathcal{K}(\cdot) \neq 1$, modifying condition (1) as follows:

$$\sum_{i=0}^{I-1} \mathcal{K}\left(e^{\varphi_{it}} \frac{q_{it}}{q_t}\right) = \mathcal{K}(1). \tag{34}$$

Needless to say, this definition also nests the main definition given in the main text with the additional condition $\mathcal{K}(\cdot) = 1$.

To invert the demand, for any collection of $(\boldsymbol{p}_t, \boldsymbol{s}_t)$ at time t, we need to solve for the vector $(\log \widetilde{q}_{it})_i$, such that:

$$\log s_{it} = \log \widetilde{q}_{it} + \psi(\log \widetilde{q}_{it}) - \log\left[\sum_{j \in V_t} \exp\left(\log \widetilde{q}_{jt} + \psi\left(\log \widetilde{q}_{jt}\right)\right)\right], \qquad \forall i \in V_t, \tag{35}$$

$$k(1) = \log\left[\sum_{i \in V_t} \exp\left(k\left(\log \widetilde{q}_{it}\right)\right)\right], \tag{36}$$

where $k(\cdot) \equiv \log \mathcal{K}(\exp(\cdot))$ and $\psi(\cdot) \equiv \log \mathcal{K}'(\exp(\cdot))$. We can rewrite Equation (35) as (assuming $O \equiv \{o\}$):

$$\log\left(\frac{s_{it}}{s_{ot}}\right) = \log\left(\frac{\widetilde{q}_{it}}{\widetilde{q}_{ot}}\right) + \psi(\log \widetilde{q}_{it}) - \psi(\log \widetilde{q}_{ot}), \qquad \forall i \in V_t. \tag{37}$$

Using the identity

$$k'(\log \widetilde{q}) = \exp\left(\log \widetilde{q} + \psi(\log \widetilde{q}) - k(\log \widetilde{q})\right),$$

we can substitute Equation (37) in Equation (36), we find:

$$\begin{aligned}
k(1) &= \log\left[\sum_{i \in V_t} \exp\left(k\left(\log \widetilde{q}_{it}\right)\right)\right], \\
&= \log\left[\sum_{i \in V_t} \exp\left(\log \widetilde{q}_{it} + \psi(\log \widetilde{q}_{it}) - k'(\log \widetilde{q}_{it})\right)\right], \\
&= \log\left[\sum_{i \in V_t} \exp\left(\log \widetilde{q}_{ot} + \psi(\log \widetilde{q}_{ot}) + \log\left(\frac{s_{it}}{s_{ot}}\right) - k'(\log \widetilde{q}_{it})\right)\right], \\
&= \log \widetilde{q}_{ot} + \psi(\log \widetilde{q}_{ot}) + \log\left[\sum_{i \in V_t} \frac{s_{it}}{s_{ot}} \exp\left(-k'(\log \widetilde{q}_{it})\right)\right], \\
&= k(\log \widetilde{q}_{ot}) + \log\left[\sum_{i \in V_t} \frac{s_{it}}{s_{ot}} \exp\left(k'(\log q_{ot}) - k'(\log \widetilde{q}_{it})\right)\right].
\end{aligned} \tag{38}$$

We use an iterative approach: starting with some initial guess for $\tilde{q}_{ot}$, we iterate between updating values of $\tilde{q}_{it}$ for $i \neq o$ from Equation (37) and updating the value of $\tilde{q}_{ot}$ from Equation (38).

A.4 The Kimball Ideal Price Index

The index h_t is tightly linked to the price index of the Kimball preferences. To see this, use the budget constraint and Equation (2) to find $e_t = h_t q_t \sum_{i=0}^{I-1} \tilde{q}_{it} \mathcal{K}'(\tilde{q}_{it})$. Define the weighted artithmetic mean of the elasticity at time t, based on the utility weight $\mathcal{K}(\tilde{q}_{it})$ implied by Kimball preferences, is equal to the weighted harmonic mean, based on the expenditure shares, and is given by

$$\begin{aligned}
\overline{\Gamma}_t &\equiv \sum_{i \in V_t} \tilde{q}_{it} \mathcal{K}'(\tilde{q}_{it}) = \sum_{i \in V_t} \left(\frac{\mathcal{K}(\tilde{q}_{it})}{\sum_{i \in V_t} \mathcal{K}(\tilde{q}_{it})} \right) \cdot \Gamma(\tilde{q}_{it}), \\
&= \frac{\sum_{i \in V_t} \tilde{q}_{it} \mathcal{K}'(\tilde{q}_{it})}{\sum_{i \in V_t} \mathcal{K}(\tilde{q}_{it})} = \frac{1}{\sum_{i \in V_t} \left(\frac{\tilde{q}_{it} \mathcal{K}'(\tilde{q}_{it})}{\sum_{i \in V_t} \tilde{q}_{it} \mathcal{K}'(\tilde{q}_{it})} \right) \frac{1}{\Gamma(\tilde{q}_{it})}} = \left(\sum_{i \in V_t} s_{it} \Gamma(\tilde{q}_{it})^{-1} \right)^{-1},
\end{aligned} \tag{39}$$

where in the last equality, we have used the fact that $s_{it} = \frac{\tilde{q}_{it} \mathcal{K}'(\tilde{q}_{it})}{\sum_{i \in V_t} \tilde{q}_{it} \mathcal{K}'(\tilde{q}_{it})}$. Letting $p_t \equiv e_t / q_t$ denote the ideal price index of the homothetic Kimball preferences defined in Equation (1), we can write it as $p_t = \overline{\Gamma}_t \cdot h_t$.

A.5 Extension to More General Preferences

We assume the following form for demand function. Given the vector of prices $\boldsymbol{p}_t$ and the total consumption expenditure e_t at time t, we assume that the expenditure share $s_{it} \equiv p_{it} q_{it} / e_t$ satisfies[54]

$$s_{it} = \frac{1}{d_t} \mathcal{S}\left(e^{-\varphi_{it}} \frac{p_{it}}{h_t}; \varsigma \right), \qquad 0 \leq i \leq I-1, \tag{41}$$

[54]We can write these conditions in terms of their duals:

$$s_{it} = \frac{1}{d_t^\dagger} \mathcal{S}^\dagger \left(e^{\varphi_{it}} \frac{q_{it}}{q_t}; \varsigma \right), \qquad 0 \leq i \leq I-1, \tag{40}$$

where the indices q_t and $d_t^\dagger$ are implicitly defined as the values satisfying: $\sum_{i=0}^{I-1} \mathcal{S}^\dagger \left(e^{\varphi_{it}} \frac{q_{it}}{q_t}; \varsigma \right) = d_t^\dagger$ and $\sum_{i=0}^{I-1} \mathcal{H}^\dagger \left(e^{\varphi_{it}} \frac{q_{it}}{q_t}; \varsigma \right) = 1$ for a monotonically decreasing functions $\mathcal{S}^\dagger(\cdot; \varsigma)$ and $\mathcal{H}^\dagger(\cdot; \varsigma)$ from $\mathbb{R}_+^I$ to $\mathbb{R}_+ \cup 0$ parameterized by a vector ς.

where the indices h_t and d_t are implicitly defined as the values satisfying:

$$\sum_{i=0}^{I-1} \mathcal{S}\left(e^{-\varphi_{it}}\frac{p_{it}}{h_t};\varsigma\right) = d_t, \tag{42}$$

$$\sum_{i=0}^{I-1} \mathcal{H}\left(e^{-\varphi_{it}}\frac{p_{it}}{h_t};\varsigma\right) = 1, \tag{43}$$

for monotonically decreasing functions $\mathcal{S}(\cdot;\varsigma)$ and $\mathcal{H}(\cdot;\varsigma)$ from $\mathbb{R}_+^I$ to $\mathbb{R}_+ \cup 0$ parameterized by a vector ς.

Note that the specification is clearly homothetic, since the expenditure shares are independent of the total expenditure e_t. This specification nests a wide array of common demand systems, including CES, Kimball (Kimball, 1995), and HSA (Matsuyama and Ushchev, 2017). The standard CES case with an elasticity of substitution σ corresponds to the choice of

$$\mathcal{S}(\widetilde{p}) \equiv \mathcal{H}(\widetilde{p}) \equiv \widetilde{p}^{1-\sigma},$$

implying $d_t \equiv 1$ and $h_t^{1-\sigma} \equiv \sum_i (e^{-\varphi_{it}} p_{it})^{1-\sigma}$.[55] The case of Kimball preferences corresponds to the following combination of functions $\mathcal{H}(\cdot)$ and $\mathcal{S}(\cdot)$ in Equation (41):

$$\mathcal{S}(\widetilde{p}) \equiv \widetilde{p} \times \left(\mathcal{K}'\right)^{-1}(\widetilde{p}), \tag{44}$$

$$\mathcal{H}(\widetilde{p}) \equiv \mathcal{K}\left(\left(\mathcal{K}'\right)^{-1}(\widetilde{p})\right), \tag{45}$$

where $d_t \equiv \sum_{i=0}^{I-1} \widetilde{p}_{it}\mathcal{D}(\widetilde{p}_{it})$. Appendix A.5.1 discusses the alternative case of the HSA family of preferences that are also nested here.

To ensure that this demand function lends itself to our procedure of demand estimation, we assume that the functions $\mathcal{S}(\cdot;\varsigma)$ and $\mathcal{H}(\cdot;\varsigma)$ are such that the demand system satisfies the connected substitutes property of Berry et al. (2013). Under this assumption, we know that we can invert the demand system to as:

$$\varphi_{it} = p_{it} - \pi_i(\boldsymbol{s}_t, \boldsymbol{p}_t; \varsigma). \tag{46}$$

Finally, we can again substitute the expression for the inverted demand in Equation (46) in Equation (19) to find:

$$p_{it} - \pi_i(\boldsymbol{s}_t, \boldsymbol{p}_t; \varsigma) - g_i(p_{it-1} - \pi_i(\boldsymbol{s}_{t-1}, \boldsymbol{p}_{t-1}; \varsigma); \varrho) = u_{it}. \tag{47}$$

[55] The corresponding dual is given by $\mathcal{S}^{\dagger}(\widetilde{q}) \equiv \mathcal{H}^{\dagger}(\widetilde{q}) \equiv \widetilde{q}^{1-1/\sigma}$.

Combining this with Equation (21) gives us a number of moment conditions that allow us to estimate the parameters of the demand ς and the process of demand shocks $\boldsymbol{\varrho}$.

The setup above nests many classes of demand systems including the Kimball preferences covered here. As another example, below we discuss the choice of HSA preferences.

A.5.1 HSA Preferences

As an alterantive to the choice of Kimball preferenecs, consider functions $\mathcal{S}(\cdot) \equiv \mathcal{H}(\cdot)$ in Equation (41) defined as the family[56]

$$\log \mathcal{S}(\widetilde{p}) \equiv -\int_{o}^{\log \widetilde{p}} \exp\left(\sum_{k=0}^{K} \theta_k x^k\right) dx, \tag{48}$$

where $\varsigma \equiv (\theta_0, \cdots, \theta_K)$ are the parameters and we have by definition $d_t \equiv 1$. Note that Equation (48) nests CES demand for the case of $\theta_0 = \log(\sigma - 1)$ and $\theta_k = 0$ for $k \geq 1$. This gives us a nonparametric deviation from the CES demand. In particular, the elasticity of demand for the product i at time t corresponding to the HSA demand in Equation (48) is given by

$$\frac{\partial \log q_{it}}{\partial \log p_{it}} = -\left[1 + \exp\left(\sum_{k=0}^{K} \theta_k \left(\log\left(\frac{p_{it}}{h_t}\right) - \varphi_{it}\right)^k\right)\right],$$

which varies from $-e^{\theta_o}$ whenever $\theta_k \neq 0$ for some $k \geq 1$.

The expression in Equation (48) for function $\mathcal{S}$ satisfies the conditions in Matsuyama and Ushchev (2017) to ensure that there exits a well-defined homothetic utility function rationalizing this demand function. We can invert this demand function to derive a corresponding function π_i in Equation (46) and combine it with Equations (47) and (21) to find the set of moment conditions that lead to estimates for the demand elasticity parameters ς and the demand shock process parameters $\boldsymbol{\varrho}$.

A.6 Comparison with Feenstra (1994)

In this section, we provide a brief comparison of the conceptual distinction between our approach and that of Feenstra (1994), which in turn builds on earlier insights of Leamer (1981). For this purpose, let us consider the CES demand specification in Section 2.3.1 that

[56] Since $d \log \mathcal{S}(\widetilde{p}) / d \log \widetilde{p} < 0$, the implication is that all products are gross substitutes everywhere.

leads to the following simple specification of demand

$$\Delta \log \widehat{q}_{it} = -\sigma \Delta \log \widehat{p}_{it} + \Delta \varphi_{it},$$

where we have defined log quantity and price relative to the base product $\widehat{q}_{it} \equiv q_{it}/q_{ot}$ and $\widehat{p}_{it} \equiv p_{it}/p_{ot}$, and where, as before, φ_{it} stands for the demand shock. The Leamer–Feenstra approach to identification begins with positing a so-called supply function relationship of the form

$$\Delta \log \widehat{p}_{it} = \zeta \log \Delta \widehat{q}_{it} + \Delta \xi_{it}, \tag{49}$$

where $\zeta > 0$ stands for the supply elasticity. The first key identification assumption is that the supply and demand shocks are uncorrelated $\mathbb{E}\left[\Delta \xi_{it} \Delta \varphi_{it}\right] = 0$. If we know the supply elasticity ζ, then this assumption leads to a synthetic instrument $z_{it}^{F-L} \equiv \Delta \log \widehat{p}_{it} - \zeta \log \Delta \widehat{q}_{it}$ that allows us to identify σ through the moment condition

$$\mathbb{E}\left[\left(\Delta \log \widehat{q}_{it} + \sigma \Delta \log \widehat{p}_{it}\right) \times z_{it}^{F-L}\right] = 0. \tag{50}$$

As shown in Feenstra (2010), the second key identification assumption is that there exists at least two products i and j for which the ratio of the variances of demand schock and supply shocks are not identical ($\mathbb{V}\left[\Delta \varphi_{it}\right] / \mathbb{V}\left[\Delta \xi_{it}\right] \neq \mathbb{V}\left[\Delta \varphi_{jt}\right] / \mathbb{V}\left[\Delta \xi_{jt}\right]$).[57] We can think of the role of this additional *identification by heteroskedasticity* assumption as that of identifying the supply elasticity ζ, which would then enable condition (50) to identify the price elasticity of demand σ. In practice, the estimation strategy combines these identification assumptions to simultaneously estimate both ζ and σ.

Now, let us compare Equation (49) with our pricing Equation (27). Assuming small relative changes in all variables, we can write the change in log price in terms of the change in log quantity and other variables as:

$$\Delta \log p_{it} \approx \underbrace{\frac{\frac{\partial \log mc_{it}}{\partial \log q_{it}} + \frac{\partial \log \mu_{it}}{\partial \log q_{it}}}{1 - \frac{\partial \log \mu_{it}}{\partial \log p_{it}}}}_{\equiv \zeta_{it}} \Delta \log q_{it} + \underbrace{\frac{\frac{\partial \log mc_{it}}{\partial \varphi_{it}} + \frac{\partial \log \mu_{it}}{\partial \varphi_{it}}}{1 - \frac{\partial \log \mu_{it}}{\partial \log p_{it}}} \Delta \varphi_{it} + \frac{\frac{\partial \log mc_{it}}{\partial w_{it}}}{1 - \frac{\partial \log \mu_{it}}{\partial \log p_{it}}} \Delta w_{it} + \Delta v_{it}}_{\equiv \Delta \xi_{it}}.$$

We can make two observations. First, in general the supply elasticity may vary over time and across products. Second, and more importantly, there are two potential grounds for the violations of the Leamer–Feenstra identification assumption $\mathbb{E}\left[\Delta \xi_{it} \Delta \varphi_{it}\right] = 0$. First,

[57] See also Soderbery (2015) for a detailed discussion of how this condition helps identify the elasticities using specific examples from trade data.

to the extent that marginal cost depends on quality, i.e., $\frac{\partial \log mc_{it}}{\partial \varphi_{it}} \neq 0$, there is a mechanical correlation between supply shocks $\Delta\xi_{it}$ and demand shocks $\Delta\varphi_{it}$. In addition, to the extent that shocks to production costs Δw_{it} leads to endogenous responses in product quality, we find another potential source of correlation between supply and demand shocks.

In contrast, our approach begins by assuming a simple dynamic process like that of Equation (20) on demand shocks. The same pricing Equation (27) now implies that $\mathbb{E}\left[\Delta u_{it} \log p_{it-2}\right]$, which leads to the following moment condition:

$$\mathbb{E}\left[\left(\Delta \log \widehat{q}_{it} + \sigma \Delta \log \widehat{p}_{it} - \rho \left(\Delta \log \widehat{q}_{it-1} + \sigma \Delta \log \widehat{p}_{it-1}\right)\right) \times \log p_{it-2}\right] = 0.$$

If we know ρ, the term $\rho\left(\Delta \log \widehat{q}_{it-1} + \sigma \Delta \log \widehat{p}_{it-1}\right)$ gives us a control function that accounts for the potential persistence between lagged price and current change in demand shocks, allowing us to identify the price elasticity σ. To recover the persistence parameter ρ, the same Equation (20) also implies that $\mathbb{E}\left[\Delta u_{it} \varphi_{it-2}\right]$ leading to another moment condition

$$\mathbb{E}\left[\left(\Delta \log \widehat{q}_{it} + \sigma \Delta \log \widehat{p}_{it} - \rho \left(\Delta \log \widehat{q}_{it-1} + \sigma \Delta \log \widehat{p}_{it-1}\right)\right) \times \varphi_{it-2}\right] = 0.$$

Just like the Leamer–Feenstra approach, we also combine the moment conditions in a GMM framework to jointly estimate both σ and ρ.

To summarize, our approach averts the need to make the counterfactual assumption that marginal costs do not depend on product quality by relying on the panel structure of the data and imposing restrictions on the dynamics of demand shocks.

B Details on the Auto Data

B.1 Data

Table 6: Summary Statistics

	Mean	Std. Dev	Min	Max
Sales	60135.09	87493.58	10	891482
Price ('000 USD)	36.18	17.47	11.14	124.05
Space	1.34	.19	.65	2
Horsepower	.53	.17	.12	1.90
Miles/$	.90	.43	.30	5.84
Luxury	.30	.46	0	1
Sport	.09	.29	0	1
SUV	.23	.42	0	1
Truck	.07	.26	0	1
Van	.06	.24	0	1
Electric	.048	.21	0	1
Observations	9493			

Note: The table displays summary statistics of the main variables of our sample of vehicles. An observation is defined as a model-year pair. Prices are in thousands of current US Dollars. Space is defined as the product between the length and the width of the vehicle in inches divided by one thousand. Horsepower is defined as the horsepower of the vehicle divided by its curbweight. Miles-per-dollar is scaled down by a factor of 10. The Electric dummy refers to EV (electric vehicles), PHEV (plug-in hybrid electric vehicles) and HEV (hybrid electric vehicles).

B.2 Testing the Identification Assumption

We are able to test the identification assumption in Equation (21) leveraging the additional data on product characteristics available for the US auto market. The identification assumption relies on the orthogonality between demand shocks innovations, u_{it}, and lagged log prices and quantities. Under the assumption in Equation (19), the identification assumption between demand shocks innovations and lagged log prices can be rewritten as:

$$\mathbb{E}\left[\varphi_{it} | g_i\left(\varphi_{it-1}; \varrho\right), \log p_{it-1}\right] = g_i\left(\varphi_{it-1}; \varrho\right) + \alpha \log p_{it-1}.$$

where α is expected to be equal to zero when the orthogonality condition holds.
Under the assumption that the demand shock process is a stationary AR(1) process, $g_i\left(\varphi_{it-1}; \varrho\right) \equiv \rho\varphi_{it-1} + (1-\rho)\,\phi_i$ as in Equation (20), we use the set of characteristics available in our

dataset as a proxy for φ_{it} and test whether the current value of product characteristics are correlated to lagged log prices after controlling for lagged characteristics. In other words, for each characteristic k, we estimate the following specification:

$$x_{kit} = \alpha \log p_{it-1} + \boldsymbol{\rho} \boldsymbol{x}_{it-1} + \eta_t + \gamma_i + \epsilon_{it}, \tag{51}$$

where $\boldsymbol{x}_{it-1}$ is the entire set of lagged product characteristics. Table (7) reports the set of coefficients estimated using Equation (51). All the estimated $\widehat{\alpha}$ coefficients are not statistically different from zero, validating our identification assumption. Moreover, all product characteristics exhibit a strong degree of autocorrelation, supporting our choice for the process of demand shocks.[58] We also standardize all variables and re-estimate Equation (51) in order to compare the coefficient of lagged price to the coefficients of lagged characteristics in terms of magnitude. Lagged product characteristics still exhibit strong and significant correlations, while lagged prices are not correlated to current product characteristics.

[58]The only exception is Truck, which exhibits a very weak autocorrelation.

Table 7: Testing the Identification Assumption

	Horse Power		Space		Miles/Dollar		Suv		Van		Truck	
Lagged	Level	Z-score	Level	Z-score	Level	Z-score	Level	Z-score	Level	Z-score	Level	Z-score
Price	0.0057	0.015	0.013	0.030	-0.024	-0.024	0.022	0.023	-0.015	-0.027	0.0092	0.016
	(0.0088)	(0.023)	(0.0078)	(0.018)	(0.019)	(0.019)	(0.027)	(0.028)	(0.011)	(0.019)	(0.0092)	(0.016)
Horse Power	0.66	0.66	-0.0040	-0.0035	0.044	0.017	-0.022	-0.0086	0.019	0.013	-0.012	-0.0079
	(0.023)	(0.023)	(0.0098)	(0.0085)	(0.025)	(0.0098)	(0.021)	(0.0086)	(0.016)	(0.011)	(0.011)	(0.0076)
Space	-0.0097	-0.011	0.63	0.63	-0.069	-0.031	-0.016	-0.0073	0.029	0.023	0.0052	0.0039
	(0.015)	(0.017)	(0.030)	(0.030)	(0.029)	(0.013)	(0.038)	(0.018)	(0.020)	(0.016)	(0.011)	(0.0086)
Miles/Dollar	0.014	0.037	-0.011	-0.025	0.53	0.53	-0.00078	-0.00080	-0.00054	-0.00095	-0.0012	-0.0020
	(0.0084)	(0.021)	(0.0057)	(0.013)	(0.055)	(0.055)	(0.0088)	(0.0090)	(0.0047)	(0.0083)	(0.0036)	(0.0062)
Suv	-0.0070	-0.017	0.0094	0.020	0.027	0.026	0.21	0.21	0.013	0.023	-0.034	-0.056
	(0.0043)	(0.011)	(0.0055)	(0.012)	(0.011)	(0.010)	(0.065)	(0.065)	(0.026)	(0.044)	(0.018)	(0.030)
Van	0.0086	0.013	0.0056	0.0071	0.013	0.0074	-0.017	-0.0098	0.18	0.18	-0.12	-0.12
	(0.0099)	(0.014)	(0.0038)	(0.0048)	(0.0074)	(0.0042)	(0.031)	(0.018)	(0.072)	(0.072)	(0.040)	(0.038)
Truck	-0.0012	-0.0018	0.014	0.019	0.0042	0.0025	-0.14	-0.086	0.10	0.11	0.10	0.10
	(0.0065)	(0.0098)	(0.0064)	(0.0085)	(0.022)	(0.013)	(0.077)	(0.047)	(0.058)	(0.060)	(0.090)	(0.090)
Observations	8268	8268	8268	8268	8268	8268	8268	8268	8268	8268	8268	8268
Model & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports the coefficients estimated using Equation (51). Each column refers to a given product characteristics. We consider horsepower, space, miles-per-dollar, truck, van and suv. For each characteristic, Equation (51) is estimated using level or z-score variables. Z-score variable refers to the set of coefficients estimated using Equation (51) after standardizing all variables. Standard errors are clustered at the model level.

B.3 Additional Tables and Figures

Table 8: BLP Coefficients

	β	σ
Price	-0.211	-
	(0.0134)	
Space	5.989	-
	(0.683)	
Horsepower	0.590	-
	(0.618)	
Miles/Dollar	0.423	-
	(0.120)	
SUV	1.182	-
	(0.200)	
Sport	1.113	-
	(0.431)	
Van	0.118	-
	(0.272)	
Truck	-0.168	-
	(0.244)	
Electric	-1.056	-
	(0.295)	
Constant	-11.20	3.34e-16
	(0.659)	(1.99e-13)
Luxury	-	2.537
		(0.177)
US Brand	-	0.969
		(0.289)

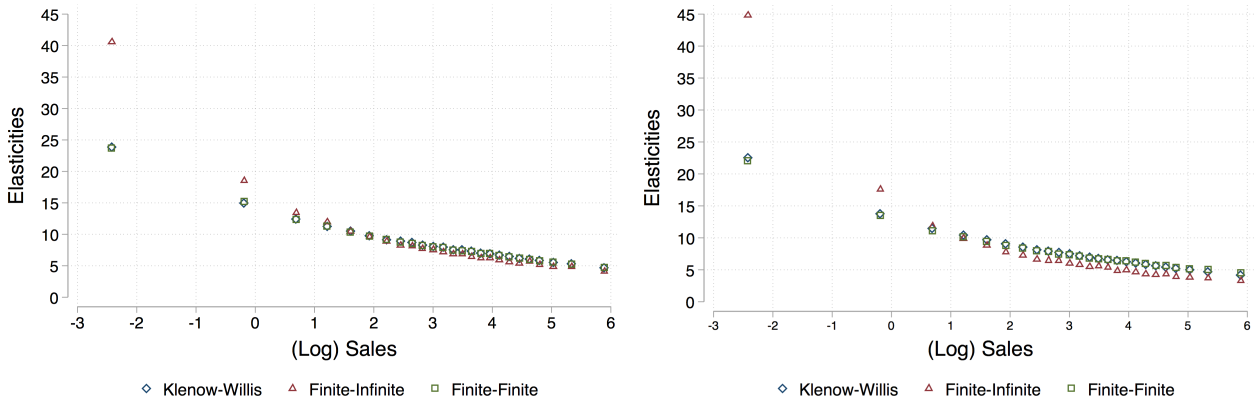
Note: The table reports the set of estimated BLP coefficients. We use the `PyBLP` package developed by Conlon and Gortmaker (2020). Weighting matrix and standard errors are clustered at the product level. Integration nodes are generate using a sparse grid of nodes and weights according to the level-six Gauss-Hermite quadrature rule. See Section 3.1 for details on how variables are defined.

Table 9: Estimates of Kimball Parameters

	Klenow-Willis		Finite-Finite		Finite-Infinite	
	DP	IV	DP	IV	DP	IV
σ	1.50	1.37	1.01	1.01	2.24	2.18
	(0.24)	(0.030)	-	-	(0.067)	(0.51)
σ_o			131	3502	2.49	2.25
			(0.050)	(1.12)	(0.11)	(0.26)
θ	0.19	0.18	0.23	0.21	0.35	0.41
	(0.030)	(0.010)	(0.0020)	(0.040)	(0.030)	(0.080)

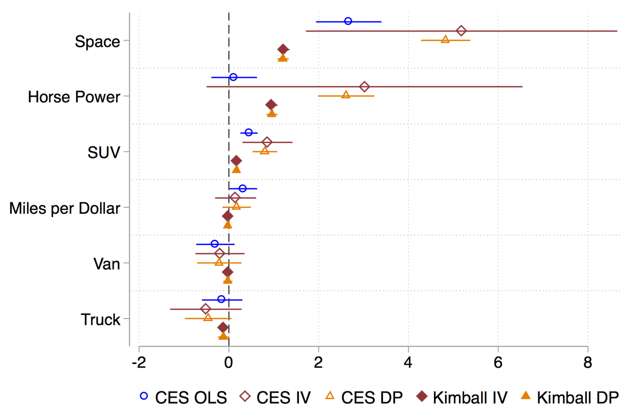
Note: The table reports the estimated Kimball coefficients for each specification with the corresponding the standard errors in parenthesis.

Figure 8: Comparison across Kimball Specifications



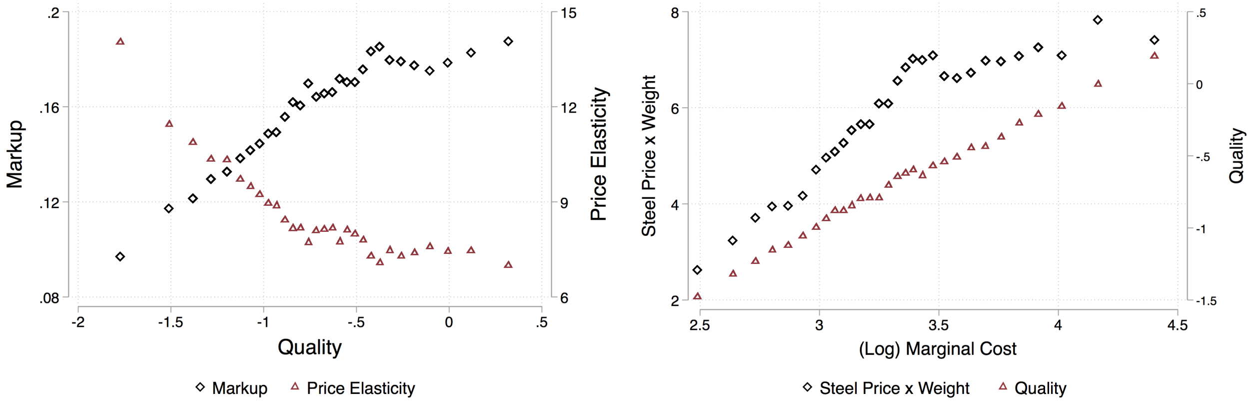
Note: The left panel shows a binscatter representation of the relationship between (log) sales and the Kimball price elasticities estimated using the DP approach. The right panel shows the relationship between (log) sales and Kimball price elasticities estimated using the IV approach. All three Kimball specifications (Finite-Finite, Finite-Infinite, and Klenow-Willis) are considered.

Figure 9: Correlation between Inferred Quality and Product Characteristics



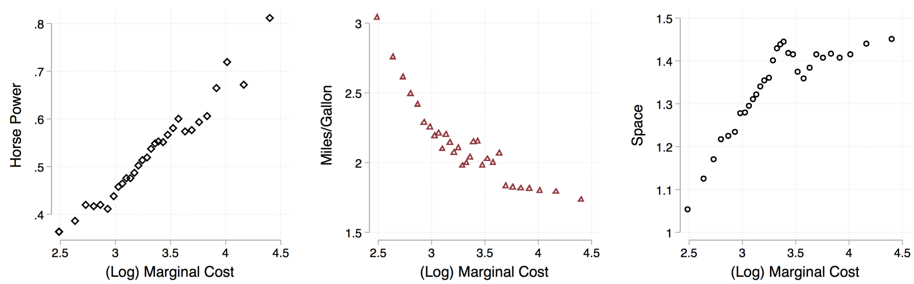
Note: The figure reports the relationship between product characteristics and inferred quality. In the CES DP case, the inferred quality measure follows from Equation (24). For the Kimball specification, inferred quality is obtained inverting demand as in Appendix *A.3*. The coefficients referring to the DP approach (CES and Kimball) and the Kimball IV case are obtained from regression in Equation (29). We consider the following product characteristics: horsepower, space, miles-per-dollar and style (suv, truck, van). The coefficients referring to the OLS and IV estimates of the CES specification are obtained from Equation (28), where product characteristics are used to proxy for quality. All regressions use the entire sample and includes time and producer fixed effects. Standard errors are clustered at producer level, the bands around the estimates show the 95% confidence intervals.

Figure 10: Markups and Marginal Cost



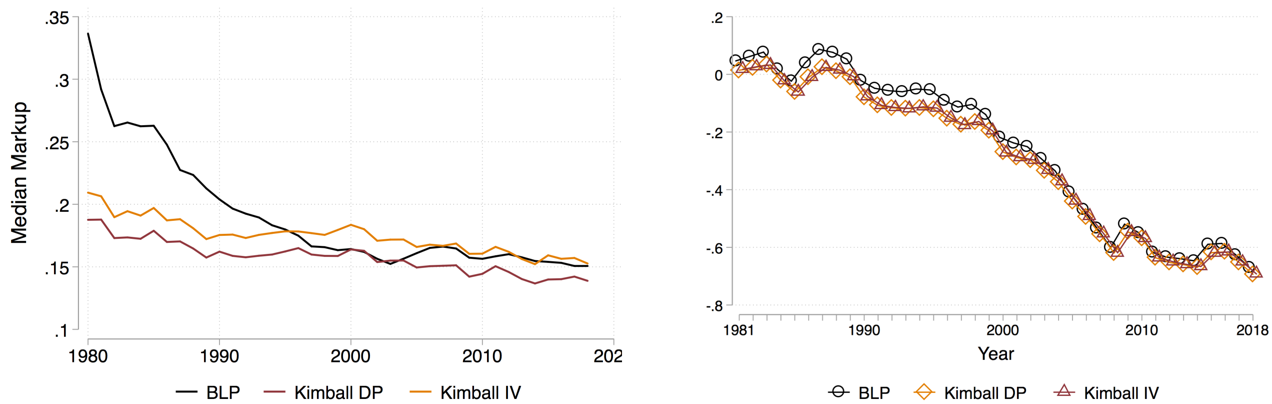
Note: The left panel shows the relationship between the measure of inferred quality and the price elasticity estimated from the Finite-Finite Kimball specification using the DP approach. Markups are computed under the assumption of monopolistic competition, $\mu_{it} = \frac{1}{\sigma_{it}-1}$, where σ_{it} is the estimated price elasticity. The right panel shows the relationship between: i) the implied marginal cost and a proxy of input costs; ii) the implied marginal cost and the measure of inferred quality estimated from the Finite-Finite Kimball specification using the DP approach. The marginal cost of each model is inferred as follow: $mc_{it} = \frac{p_{it}}{1+\mu_{it}}$. The input costs proxy is created multiplying the price of steel to the weight of each vehicle.

Figure 11: Marginal Cost and Product Characteristics



Note: Each panel shows the relationship between the inferred marginal cost and a product characteristic. We consider horsepower (left), space (center) and miles-per-gallon (right). Marginal cost is inferred from $mc_{it} = \frac{p_{it}}{1+\mu_{it}}$, where μ_{it} is the markup computed under the assumption of monopolistic competition using the price elasticities estimated from the Finite-Finite Kimball specification using the DP approach.

Figure 12: Trends in Markups and Marginal Cost



Note: The left panel shows the evolution of the median markup over the period 1980-2018. Markups are computed under the assumption of monopolistic competition, $\mu_{it} = \frac{1}{\sigma_{it}-1}$, where σ_{it} is the estimated price elasticity. The BLP and Finite-Finite Kimball specifications are considered. The right panel shows the estimated trend in the real marginal cost. The real marginal cost is computed from $mc_{it} = \frac{p_{it}}{1+\mu_{it}}$ and deflated using the CPI. The trend in the marginal cost is obtained regressing the inferred marginal cost at the model-year level on product characteristics and a time trend.

Table 10: Ideal Price Index for the US Auto Market: CES vs Kimball

	Total		Decomposition				
			Price	Quality		Variety	
	Kimball	CES		Kimball	CES	Kimball	CES
Cumulative Change (%)	-127.3	-269.0	-60.1	-49.6	-175.9	-17.5	-32.9
Annual Change (%)	-3.35	-7.08	-1.58	-1.31	-4.63	-0.46	-0.87

Note: The Table reports the cumulative and the average annual change in the ideal import price indices for the auto market over the period 1980-2018 and its decomposition into the price, quality and variety channels. Prices are deflated using the CPI index from BLS. Quality is normalized such that the average change in quality of the set of continuing models that are not redesigned is zero. The price index is computed for both the Kimball and the CES specifications, estimated using the DP approach.

C Details on the US Import Data

C.1 Further Examination of CES Estimates

Price Elasticities Across Different Levels of Aggregation Table 11 reports the mean and the median of the estimated elasticities using the DP approach for three different levels of product aggregation. As expected, we find lower elasticities when we aggregate products in broader categories. The average elasticity is 4.5 at the SITC3 level and it increases to 5.6 at the HS10 level. Even if the differences appear small, we can statistically reject the null hypothesis that the mean elasticiticies are the same across all level of aggregations. Note also that the median elasticities of substitution exhibit the same qualitative pattern, as their values increase from 2.9 to 3.4. The median estimates at more aggregate levels (three and five digit) statistically differ from the most disaggregated level.[59]

Table 11: CES Elasticities based on the DP Approach at Different Levels of Aggregation

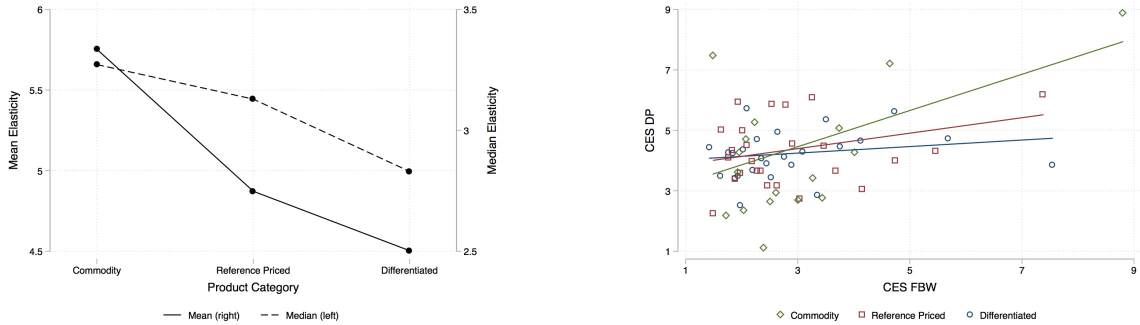
	HS10	SITC5	SITC3
Mean	5.65	5.09	4.49
(SE)	(0.09)	(0.21)	(0.40)
Median	3.37	3.13	2.87
(SE)	(0.05)	(0.10)	(0.23)
N	8508	1296	147
T-statistics		2.493	2.836
Pearson χ^2 p-value		0.043	0.025

Note: Mean and median of the elasticities of substitution estimated with the DP approach for the products defined at the HS10, SITC5 and SITC3 levels of aggregation. Only feasible estimates are reported. Values above 130 are censored. Standard errors for each statistics are bootstrapped. T-statistics refer to a t-test for differences in mean with respect to the HS10 level; p-values for Pearson difference in median tests with respect to the HS10 level.

Price Elasticities Across Different Rauch (1999) Product Classes We use the Rauch (1999) classification to distinguish products at the SITC4 level into three categories: commodities, referenced priced, and differentiated goods. Rauch (1999) provides two distinct classification, "Liberal" and "Conservative", that only differ in the classification of few products that, in principle, can be classified in multiple ways. The left panel of Figure 13 shows both the mean and the median elasticity for each Rauch Conservative category. Both these statistics are ranked in increasing order between commodities, referenced priced, and differentiated products, as expected. We can reject the hypothesis that

[59]In contrast to the case of the mean estimates, we cannot statistically reject the hypothesis that the medians are the same at the SITC3 and SITC5 level.

Figure 13: DP Elasticities and Rauch Conservative Classification



Note: The left panel displays the mean and the median of the elasticities of substitution estimated with the DP approach for each category of the Rauch Conservative Classification at the SITC4 level of aggregation. The right panel shows the correlation between the DP and FBW estimates for each category of the Rauch Conservative Classification at the SITC4 level of aggregation.

the combined set of commodities and referenced priced goods have the same mean or median than differentiated products.[60] Table 12 reports the corresponding values and their standard errors for Figure 13 and show that qualitative results holds also for the Liberal version of the classification.

In addition, again using the classification proposed by Rauch (1999), we can show that the quality bias in the convential estimates is stronger among more differentiated products. Intuitively, quality differentiation is less likely among homogeneous goods, suggesting that the DP estimates in this case should on avearge be closer to, and more correlated with, the conventional estimates. Consistently with this intuition, the right panel of Figure 13 shows that the correlation between DP and FBW is stronger for commodities and the average difference between the two sets of estimates is smaller. As we consider less homogenous categories, referenced priced and differentiated products, the average quality bias increases while the correlation decreases.[61] Figure 14 shows that the qualitative pattern is robust to how products are grouped between homogenous and differentiated.

[60] We statistically test the difference between differentiated products and the remaining categories pooled together. Differences are not statistically significant if the two categories are considered individually.

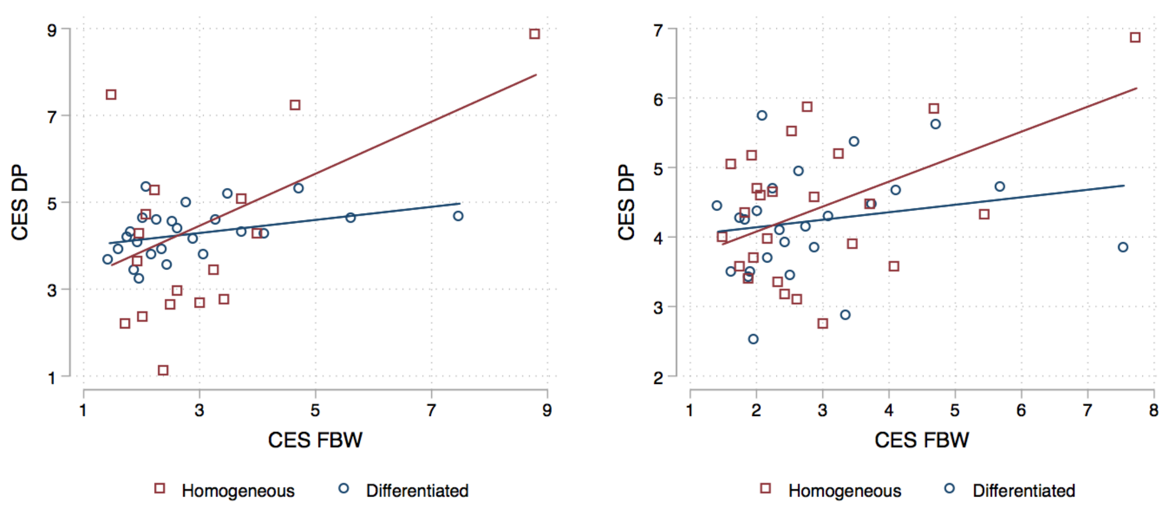
[61] The average difference between group captures the average quality bias and is represented by the intercept of a linear regression (fitting line). The slope would capture instead the correlation across estimates.

Table 12: DP Estimates: Rauch Classifications

	Commodity	Reference Priced	Differentiated		Commodity	Reference Priced	Differentiated
Mean	5.75	4.87	4.50	Mean	5.28	4.77	4.58
(SE)	(0.86)	(0.42)	(0.25)	(SE)	(0.63)	(0.42)	(0.27)
Median	3.27	3.13	2.83	Median	3.24	3.10	2.82
(SE)	(0.69)	(0.18)	(0.18)	(SE)	(0.37)	(0.18)	(0.21)
N	50	168	317	N	75	162	298

Note: For each category of the Rauch Classification (commodity, reference priced and differentiated), the tables report the mean and the median CES elasticity estimated using the DP approach at the SITC4 level. The left panel refers to the Conservative version of the classification (corresponding to Figure 13 in the main text) while the right one to the Liberal version. It can be show that differences in mean and median are statistically significant at standard levels if the more homogeneous categories (commodities and reference priced) are pooled together and compared to differentiated products.

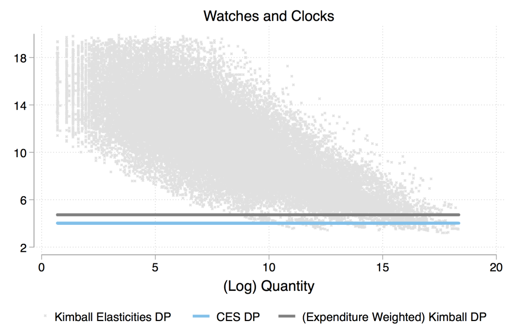
Figure 14: Correlation DP and FBW, Different Pooling of Rauch Categories



Note: The figure shows the correlation between the estimated elasticities using the DP and FBW methods at the SITC4 level using alternative breakdowns across products. Conservative Rauch classification is used. In the left panel, homogeneous products are defined as commodities only while, in the right panel, they include commodieties and reference priced goods.

C.2 Additional Tables and Figure on Kimball Elasticities

Figure 15: CES-Kimball Elasticity: Watch and Clocks



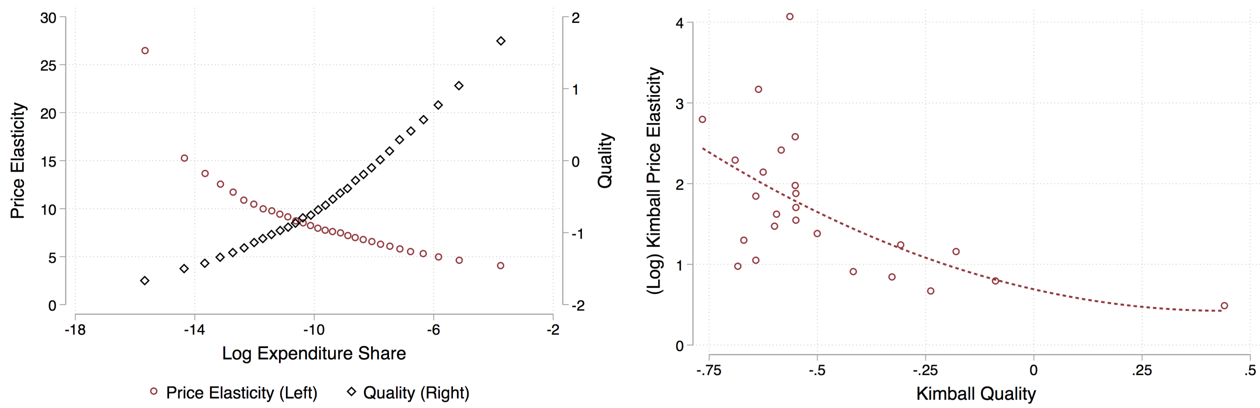
Note: The figure shows the entire set of Kimball price elasticities of each variety-time pair, σ_{it}, as a function of the (log) quantity imported for the sector Watches and Clocks (SITC3 884). The gray line represents the expenditure-weighted mean Kimball price elasticity while the blue line represents the CES estimated elasticity for the sector.

Table 13: Kimball Parameters

	σ	σ_0	θ
Mean	1.99	651.2	0.73
	(0.13)	(156.1)	(0.23)
Median	1.12	8.13	0.16
	(0.054)	(1.12)	(0.017)

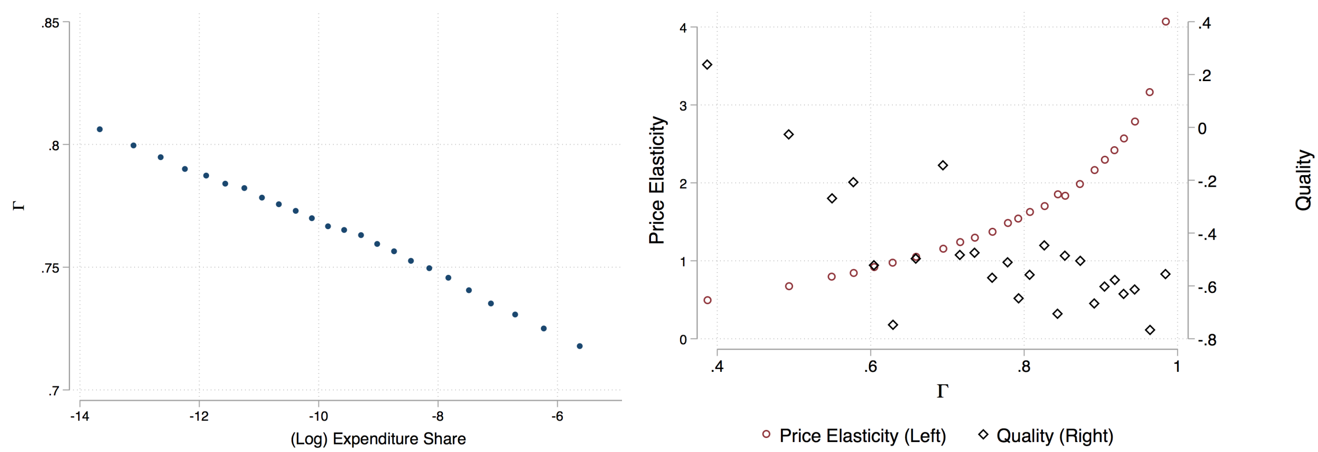
Note: The table displays the mean and the median across all SITC3, with the corresponding standard errors, of the estimated parameters of the Finite-Finite Kimball specification.

Figure 16: Kimball Price Elasticities and Implied Quality



Note: The left panel plots the binscattered relationship between (log) expenditure share of each variety-time observation and the Kimball price elasticity (left axis) and product quality (right axis). The right panel directly plots the relationship between product quality and price elasticity.

Figure 17: Kimball Elasticity

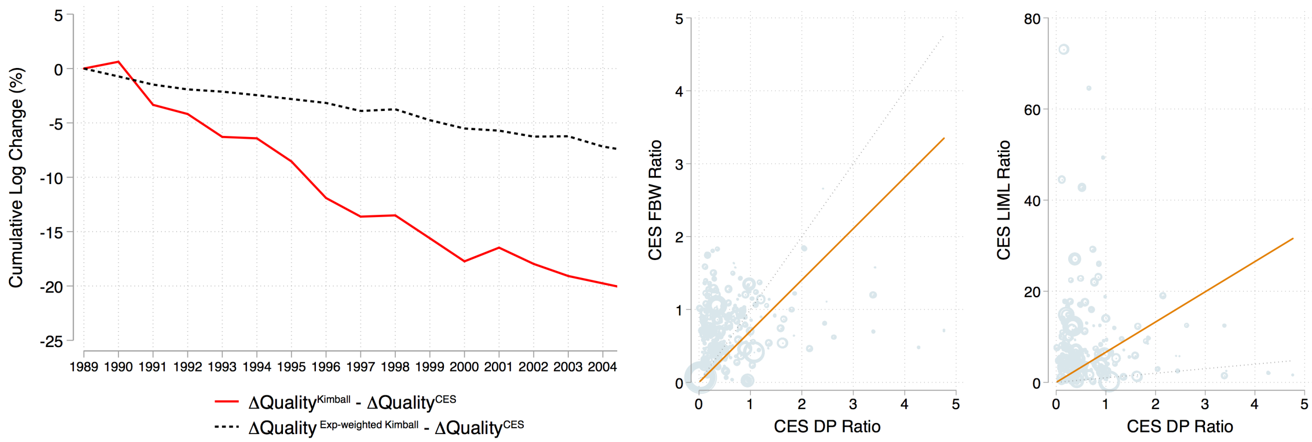


Note: The figure plots the binscattered relationship between the Kimball elasticity of each variety-time observation, Γ_{it}, and the (log) expenditure share (left panel), product quality (right panel, left axis) and Kimball price elasticity (right panel, right axis).

C.3 Further Results on Welfare and Quality Decomposition

Bias in Inferred Quality: CES Estimates of FBW-LIML vs DP The left panel of Figure 18 shows the gap between in the Torqvist-weighted mean quality change between the inferred quality using Kimball and that under CES when, instead of the full set of Kimball price elasticities σ_{it}, we use the expenditure weighted average Kimball elasticity for all varieties within each sector. In this counterfactual scenario, the cumulative gap between Kimball and CES quality declines to around 7%, as reported in Table 14, in line with the relevance of the heterogeneity bias affecting the CES estimated elasticities.

Figure 18: Quality Contribution: Alternatives to Kimball



Note: The left panel shows the gap between in the Torqvist-weighted mean quality change between the inferred quality using Kimball and that under CES when, instead of the full set of Kimball price elasticities, we use the expenditure weighted average Kimball elasticity for all varieties within each sector. The right panel plots the Tornqvist-weighted cross-sector correlation between the DP elasticity ratio, $\frac{1}{\sigma_k^{DP}-1}$, and the FBW and LIML elasticity ratios ($\frac{1}{\sigma_k^{FBW}-1}$ and $\frac{1}{\sigma_k^{LIML}-1}$, respectively) for the CES specification. The dotted line represents the 45 degrees line.

Using the approximation in Proposition 2, we compute the gap between in the Torqvist-weighted mean quality change between the inferred quality using the DP and the FBW-LIML estimates of CES elasticities. When we compare two sets of CES elasticities, the first term of the decomposition, the gap in the love-of-variety proxies, is the only driver since all the heterogeneity in price elasticities disappears. The gap in the Torqvist-weighted mean quality change boils down to the difference in the estimated price elasticities, or, more precisely, in $\frac{1}{\sigma_k^{DP}-1}$ and $\frac{1}{\sigma_k^{FBW}-1}$ or $\frac{1}{\sigma_k^{LIML}-1}$. The right panel of Figure 18 plots the Tornqvist-weighted cross-sector correlation between the DP elasticity ratio and the FBW and LIML elasticity ratios. The LIML ratios are substantially higher than the DP ones, consistent with the fact that the LIML elasticities are smaller than the DP ones. The weighted correlation is slightly smaller than one in the case of the FBW estimates, in line with the fact that the FBW elasticities are upward biased with respect to the LIML one and, thus, closer to the DP values. Table 14 quantifies the gap arising from the differences in the elasticity ratios: using the LIML estimated elasticities instead of the DP ones would largerly underestimate the contribution of quality while the gap is much smaller if we use the FBW estimates, in line with the average values of the estimated elasticities.

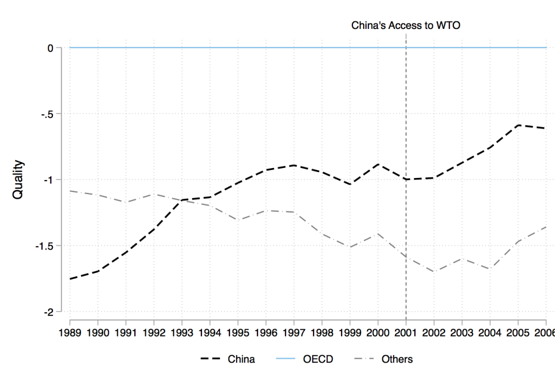
Table 14: Quality Contribution: Average Kimball vs CES

	Difference in Quality Contribution (%)
DP:	
Kimball - CES	-20.4
Average Kimball - CES	-7.36
CES:	
FBW - DP	-0.60
LIML - DP	605.4

Note: The table reports the cumulative gap between in the Torqvist-weighted mean quality change between: i) the inferred quality using the expenditure-weighted average Kimball elasticities and that under CES; ii) the inferred quality under CES estimated using the DP approach and the FBW method; iii) the inferred quality under CES estimated using the DP approach and the LIML method.

Quality Decomposition Figure 19 shows the evolution of the expenditure-weighted quality for each (group of) exporter(s), China, OECD economies and all other countries. The (expenditure-weighted) average quality of Chinese varieties has increased constantly since 1989 relative to the average OECD quality, which is normalized to zero over the entire time period. This supports the extensive evidence that Chinese goods have undergone a sophistication process, catching up with more advanced economies and largely contributing to the aggregate quality improvement of US imports.

Figure 19: Decomposition of Quality across Countries



Note: The figure shows the evolution of the (expenditure weighted) average quality of each (group of) exporter(s), China, OECD economies and rest of the world. OECD (expenditure weighted) average quality is normalized to zero for exposition.

Table 15 shows that import quality has increased by around 28% over the time period from 1989 to 2006. This increase is exclusively driven by a rise in quality within each (group of) exporter(s) while compositional changes between exporters partially offset the within forces. This is consistent with the fact that Chinese products gained market share over the time period but still have lower quality compared to other exporters, even if they are catching up with the frontier. Notice also that the annual increase in quality is larger after China joined the WTO in 2001, suggesting that the trade liberalization shock boosted the sophistication process even more.

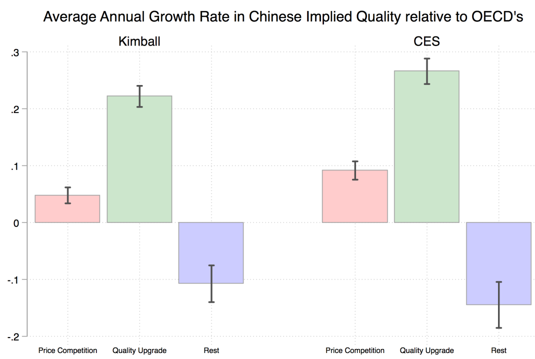
Table 15: Between and Within Decomposition

	$\Delta\varphi$	Δ within	Δ between
Full Sample	0.283	0.424	-0.141
Before 2001	0.159	0.227	-0.068
After 2001	0.124	0.197	-0.073

Note: The Table shows a decomposition of the growth in aggregate product quality between and within exporters. We consider China, OECD economies and all the other exporters pool together. For each exporter, we compute the aggregate product quality as the expenditure-weighted average across varieties.

Finally, we also check how the quality of Chinese varieties relative to OECD's evolved for each category defined in Figure 27, quality upgrading, price competition and others. For each product category (HS8), we compute the average annual change in inferred quality of Chinese varieties relative to the set of advanced economies used for Figure 27. Consistent with their definition, the change in quality of Chinese products labelled as "quality upgrading" is four times larger than the change in quality of Chinese products labelled as "price competition". This confirms the intuition that quality improvements represent the key mechanism to explain the increase in Chinese import penetration and the simultaneous rise in relative prices. The specifcation of demand has first-order effect on our measurement of the role of quality as the quality improvements inferred from CES are larger for all three categories (right panel).

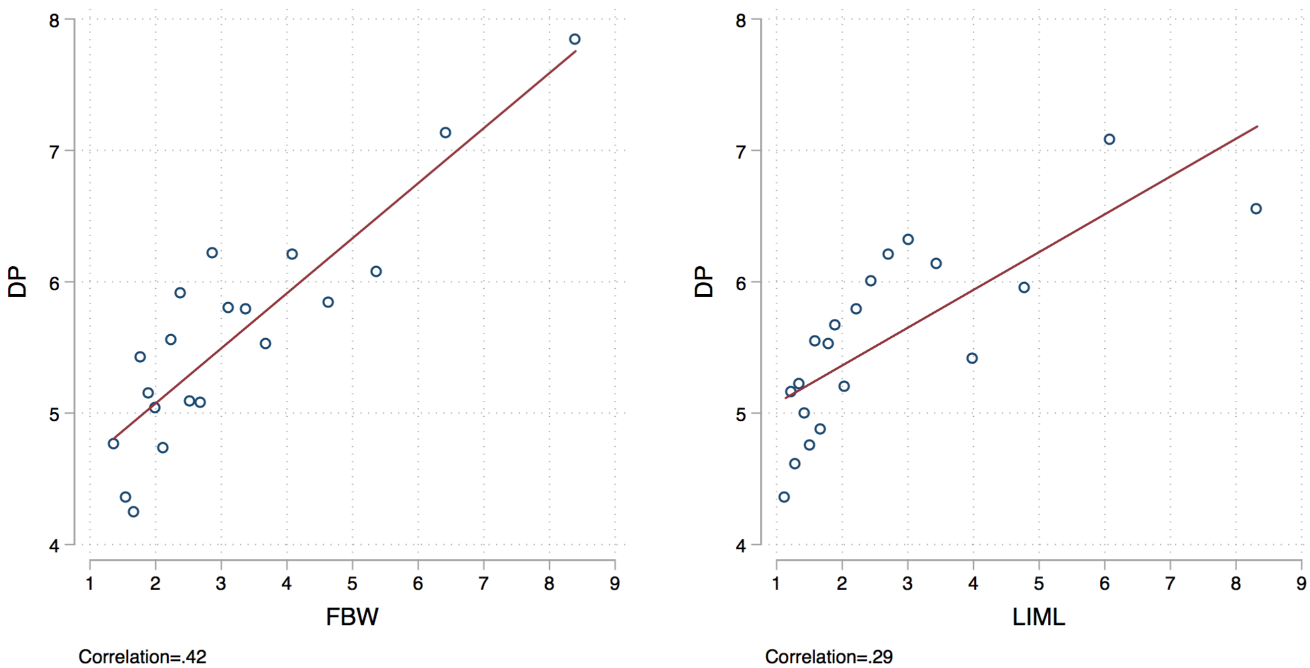
Figure 20: Inferred Quality: Quality Upgrading and Price Competition



Note: The figure shows the average annual product quality growth rate across Chinese varieties defined at the HS8 level, relative to the average annual growth rate of the corresponding OECD variety. Left (right) panel uses inferred quality from Kimball (CES) specification. Product categories "Quality Upgrade", "Price Competition", and "Rest" are defined in Figure 27.

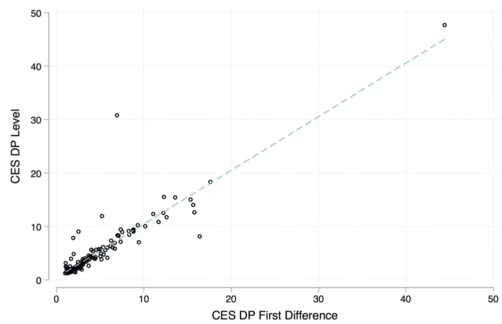
C.4 Additional Tables and Figures

Figure 21: Correlation between DP and FBW or LIML Estimates, HS10 level



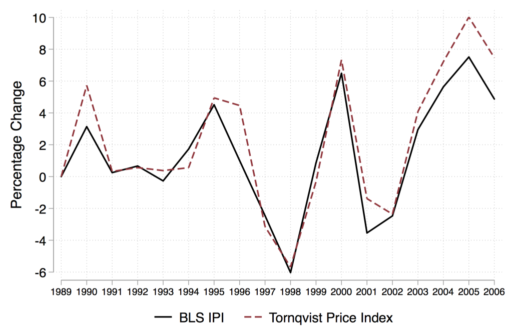
Note: The figure shows the correlation between the estimated elasticities using the DP approach and conventional methods like FBW (right panel) and LIML (left panel). The figures refers to the set of estimates at the HS10 level. Elasticities are censored at 10.

Figure 22: Comparison CES Estimate: Level vs First Difference Moment



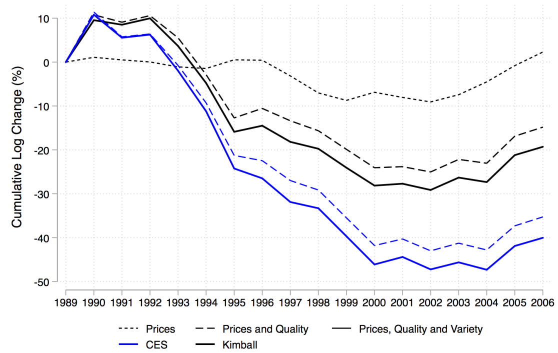
Note: The figure shows the correlation between the estimated CES elasticities obtained using CES as the limiting Kimball moment ($\sigma_o \equiv \sigma$) and the first difference moment used for the elasticities reported in Table 11. Dashed line represents the 45 degrees line.

Figure 23: Comparison with BLS Import Price Index



Note: The figure plots the year-to-year change in the BLS Import Price Index and a the price component of the aggregate import price constructed using the Tornqvist approximation.

Figure 24: Dynamics of US Import Price Index - PPI Deflated



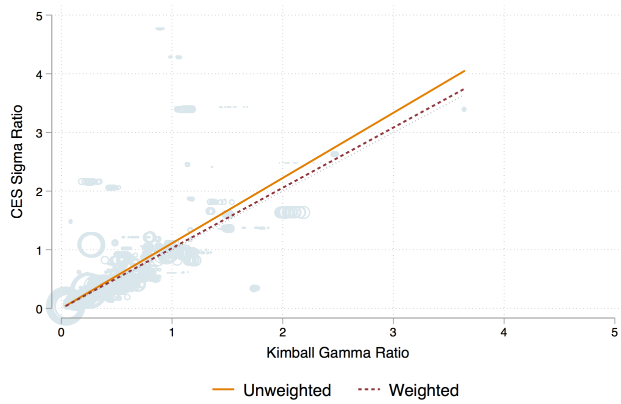
Note: The figure plots the aggregate import price indices for both the CES and the Kimball specifications and their decomposition into the price, quality and variety components, according Equations (14) and (15). Prices are deflated using the PPI index from BLS. The measure of inferred quality is normalized such that the average quality of the set of OECD varieties is zero. The solid lines represent the aggregate import price index including all three components. The dashed and dotted lines represent the price and quality components together and the price component only, respectively. Black (Blue) lines refer to the Kimball (CES) specification.

Table 16: Welfare Gains from Trade - PPI Deflated

	Total		Decomposition				
			Price	Quality		Variety	
	Kimball	CES		Kimball	CES	Kimball	CES
Cumulative Change (%)	-19.3	-40.0	2.29	-17.1	-37.6	-4.48	-4.76
Annual Change (%)	-1.07	-2.22	0.13	-0.95	-2.09	-0.25	-0.26

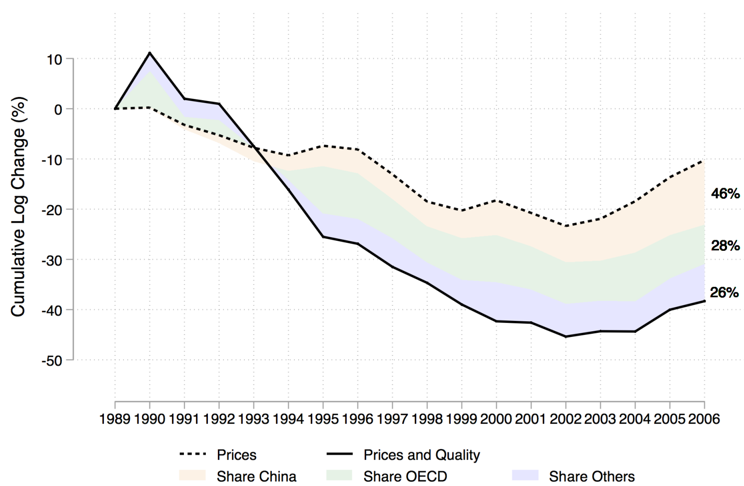
Note: The Table reports the cumulative and the average annual change in the aggregate import price indices defined in Equations (14) and (15) and reported in Figure 24, and their decomposition. Prices are deflated using the PPI index from BLS. The measure of inferred quality is normalized such that the average quality of the set of OECD varieties is zero.

Figure 25: CES and Kimball Weights for Lambda Ratio



The figure shows the cross-sector (SITC3) correlation between $\frac{1-\bar{\Gamma}^*_{kt}}{\bar{\Gamma}^*_{kt}}$ (Kimball Gamma Ratio) and $\frac{1}{\sigma_k - 1}$ (CES Sigma Ratio). The solid (dashed) line represents the unweighted (weighted) correlation coefficients. The dotted line is the 45 degrees line. Both correlation coefficients are greater than and statistically different from one. For the weighted correlation coefficients, observations are weighted using the Tornqvist weights of each SITC3 sector.

Figure 26: Price Index, Decomposition of Quality across Countries: CES case



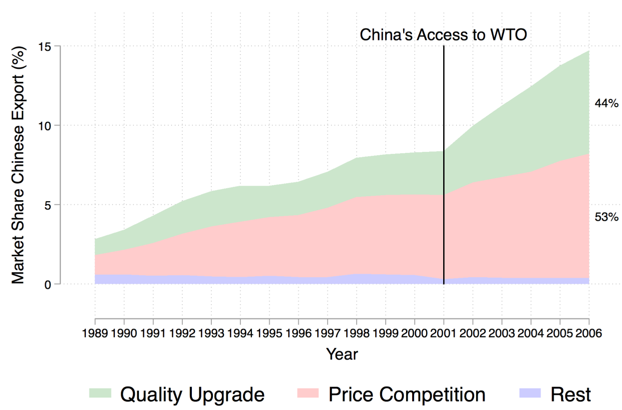
Note: The dashed line figure shows the price component of the aggregate import price index. The solid line shows the price component and the quality component of the aggregate import price index. The quality contribution is computed using the inferred quality from the CES specification. The difference between these two lines quantifies the role of product quality change and is decomposed into the role of Chinese varieties (orange area), OECD varieties (green area) and all other varieties pooled together (purple area).

D Additional Tables and Figure

D.1 Examining the Share of China in US Imports

Figure 27 shows that the evolution of the aggregate import share of Chinese products, decomposing the change in the import share into three categories. We distinguish the market share of those products whose prices and market share have both increased relative to a set of benchmark origin countries ("quality upgrade" products), the market share of those products with rising market share but falling relative price ("price competition" products), and the market share of those products with falling market share and relative price ("rest" products). The aggregate import share of Chinese products increased up to 15% in 2006. Around 46% of the growth in the aggregate import share of Chinese products over the period 1989-2006 stems from the contributions of the first group ("quality upgrade" products).

Figure 27: Decomposition of Chinese Export: Quality Upgrade and Price Competition

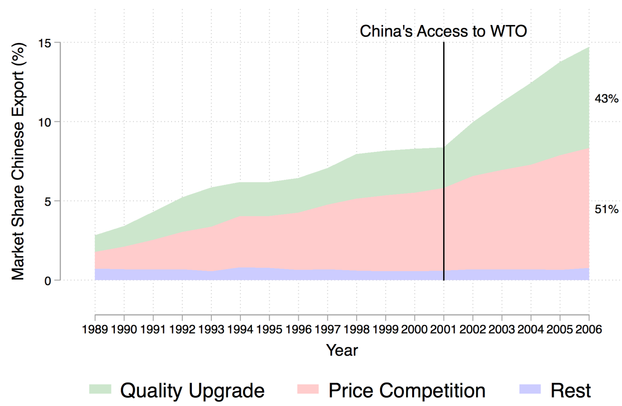


Note: The figure shows the decomposition of Chinese import share into three categories: Quality Upgrade, Price Competition and Rest. Quality Upgrade represents the market share of Chinese products whose both market share and relative price increased over time on average. Price Competition includes those products whose market share increased but relative price declined over time. The third category (Rest) includes the remaining products, that is, products whose market share declined over time. Relative prices are defined with respect to the average price across the varieties imported from a set of advanced economies, including Canada, Japan, Germany, United Kingdom, Switzerland, Italy, France, Belgium, Netherland, Spain, Austria, Denmark, Finland, Portugal, Sweden, Norway, Ireland, Iceland, Greece, Australia and New Zealand. Products classified at the 8-digit level of the Harmonized System classification.

Relative prices are defined with respect to the average price across the varieties imported from a set of advanced economies, including Canada, Japan, Germany, United Kingdom, Switzerland, Italy, France, Belgium, Netherland, Spain, Austria, Denmark, Finland, Portugal, Sweden, Norway, Ireland, Iceland, Greece, Australia and New Zealand. Products classified at the 8-digit level of the Harmonized System classification. Below, we show that the pattern in Figure 27 holds quantitatively when products are classified at the 10-digit level of the HS classification and considering alternative basket of countries as benchmark, such as all OECD economies, all advanced economies as classified by the IMF and individual countries like Germany or Japan.

Figure 29 and Table 19 show that the same pattern is stronger in industries where product quality and differentiation may play a stronger role, such as Machinery and Transportation. In addition, Table 17 shows that most of the growth due to quality upgrade took place after China's access to WTO in 2001.

Figure 28: Decomposition Chinese Export, 10-digit level product codes



Note: The figure shows the decomposition of Chinese import share into three categories: Quality Upgrade, Price Competition and Rest. Quality Upgrade represents the market share of Chinese products whose both market share and relative price increased over time on average. Price Competition includes those products whose market share increased but relative price declined over time. The third category (Rest) includes the remaining products, that is, products whose market share declined over time. Relative prices are defined with respect to the average price across the varieties imported from a set of advanced economies, including Canada, Japan, Germany, United Kingdom, Switzerland, Italy, France, Belgium, Netherland, Spain, Austria, Denmark, Finland, Portugal, Sweden, Norway, Ireland, Iceland, Greece, Australia and New Zealand. Products classified at the 10-digit level of the Harmonized System classification.

Table 17: Decomposition Chinese Export, Pre and Post 2001

	Full Sample	Before 2001	After 2001
Yearly Market Share Growth Rate	10.5	9.90	12.0
Share Quality Upgrade	46.1	31.7	58.7
Share Price Competition	55.6	73.4	39.9
Rest	-1.67	-5.13	1.37

Notes: Quality Upgrade, Price Competition and Rest. Quality Upgrade represents the market share of Chinese products whose both market share and relative price increased over time on average. Price Competition includes those products whose market share increased but relative price declined over time. The third category (Rest) includes the remaining products, that is, products whose market share declined over time. Relative prices are defined with respect to the average price across the varieties imported from a set of advanced economies, including Canada, Japan, Germany, United Kingdom, Switzerland, Italy, France, Belgium, Netherland, Spain, Austria, Denmark, Finland, Portugal, Sweden, Norway, Ireland, Iceland, Greece, Australia and New Zealand. Products classified at the 8-digit level of the Harmonized System classification.

Figure 29: Decomposition Chinese Export, by Sector

Notes: Quality Upgrade, Price Competition and Rest. Quality Upgrade represents the market share of Chinese products whose both market share and relative price increased over time on average. Price Competition includes those products whose market share increased but relative price declined over time. The third category (Rest) includes the remaining products, that is, products whose market share declined over time. Relative prices are defined with respect to the average price across the varieties imported from a set of advanced economies, including Canada, Japan, Germany, United Kingdom, Switzerland, Italy, France, Belgium, Netherland, Spain, Austria, Denmark, Finland, Portugal, Sweden, Norway, Ireland, Iceland, Greece, Australia and New Zealand. Products classified at the 8-digit level of the Harmonized System classification. Food & Chemicals refers to the one digit industries 0 to 5 of SITC classification pooled together, Manufacturing Materials to industry 6, Machinery to industry 7, Miscellaneous Manufacture to industry 8. Industry 9 (Miscellanea) is dropped.

Table 18: Decomposition Chinese Export, by Sector

	Aggregate	Food & Chemicals	Manufacturing Materials	Machinery	Misc Manufacture
Yearly Market Share Growth Rate	10.5	3.15	12.6	18.2	8.46
Share Quality Upgrade	46.1	62.2	51.3	54.2	27.3
Share Price Competition	55.6	118.9	51.0	45.1	71.7
Rest	-1.67	-81.1	-2.25	0.70	0.96

Notes: Quality Upgrade, Price Competition and Rest. Quality Upgrade represents the market share of Chinese products whose both market share and relative price increased over time on average. Price Competition includes those products whose market share increased but relative price declined over time. The third category (Rest) includes the remaining products, that is, products whose market share declined over time. Relative prices are defined with respect to the average price across the varieties imported from a set of advanced economies, including Canada, Japan, Germany, United Kingdom, Switzerland, Italy, France, Belgium, Netherland, Spain, Austria, Denmark, Finland, Portugal, Sweden, Norway, Ireland, Iceland, Greece, Australia and New Zealand. Products classified at the 8-digit level of the Harmonized System classification. Food & Chemicals refers to the one digit industries 0 to 5 of SITC classification pooled together, Manufacturing Materials to industry 6, Machinery to industry 7, Miscellaneous Manufacture to industry 8. Industry 9 (Miscellanea) is dropped.

Table 19: Decomposition Chinese Export: Pre and Post 2001, by Sector

	Food & Chemicals	Manufacturing Materials	Machinery	Misc Manufacture
Full Sample				
Yearly Market Share Growth Rate	3.15	12.6	18.2	8.46
Share Quality Upgrade	62.2	51.3	54.2	27.3
Share Price Competition	118.9	51.0	45.1	71.7
Rest	-81.1	-2.25	0.70	0.96
Before 2001				
Yearly Market Share Growth Rate	1.50	11.4	16.5	8.32
Share Quality Upgrade	125.8	52.9	31.5	22.5
Share Price Competition	272.7	54.1	69.6	77.2
Rest	-298.4	-7.02	-1.06	0.33
After 2001				
Yearly Market Share Growth Rate	7.08	15.5	22.5	8.77
Share Quality Upgrade	40.1	50.1	65.1	32.9
Share Price Competition	65.7	48.9	33.3	65.4
Rest	-5.88	1.04	1.54	1.68

Notes: Quality Upgrade, Price Competition and Rest. Quality Upgrade represents the market share of Chinese products whose both market share and relative price increased over time on average. Price Competition includes those products whose market share increased but relative price declined over time. The third category (Rest) includes the remaining products, that is, products whose market share declined over time. Relative prices are defined with respect to the average price across the varieties imported from a set of advanced economies, including Canada, Japan, Germany, United Kingdom, Switzerland, Italy, France, Belgium, Netherland, Spain, Austria, Denmark, Finland, Portugal, Sweden, Norway, Ireland, Iceland, Greece, Australia and New Zealand. Products classified at the 8-digit level of the Harmonized System classification. Food & Chemicals refers to the one digit industries 0 to 5 of SITC classification pooled together, Manufacturing Materials to industry 6, Machinery to industry 7, Miscellaneous Manufacture to industry 8. Industry 9 (Miscellanea) is dropped.