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 method that allows us to identify demand and to infer unobserved quality change using data only on prices and market shares. Our method applies to a wide class of homothetic demand systems that allow for heterogeneity in the degree of substitutability across products. For this class, we also characterize the contribution of changes in quality, price, and variety entry/exit to the aggregate price index. To validate our approach, we show that it estimates price elasticities and quality changes similar to those found by the standard BLP strategy in data on the US auto market, without relying on the information on product characteristics and price instruments used by BLP. Applying our strategy to the US customs data (1989–2006), we find the average contributions of quality, price, and variety to the annual fall in the price of US imports relative to CPI to be 0.95%, 0.60%, and 0.25%, respectively. 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 any given country using available customs records on the volumes and unit values of all imported products. The data allows us to construct aggregate indices for the price of imports that transform the observed changes in the volume and variety of imported products into measures of real consumption gain (Feenstra, 1994; Broda and Weinstein, 2006). However, these indices often leave out yet another potential margin for consumption gains through improvements in the quality of each imported product over time. Part of the challenge for evaluating the extent of quality change lies in the fact that customs records, despite their richness, typically lack comprehensive information on product characteristics.

As an example for the potential magnitude of the quality margin, 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 be tempted to attribute this rise mostly to the gradual availability of cheaper Chinese varieties to US consumers. Surprisingly, however, we find that roughly half of the overall rise in the Chinese share of US imports over this period comes from those products where the prices of Chinese varieties increased relative to advanced countries.[1] This fact suggests that quality upgrading in Chinese imports may have played a crucial role in their rising appeal for US consumers and importers, while being left out of standard measures that evaluate their value for consumers (e.g., the BLS import price index).

More broadly, the problem of accounting for unobserved quality change applies to many macro settings where we aggregate observed changes in quantities and prices across a wide range of products with limited data on their characteristics.[2] In this paper, we develop and implement a novel strategy to address this problem. Our approach builds on the prior insight that product quality may be inferred as the residual demand after accounting for the contribution of prices (Khandelwal, 2010; Hallak and Schott, 2011), and thus requires the estimation of the demand function. We show how to estimate flexible demand functions and to infer product quality if the data only contains information on prices and market shares. We use our method to quantify the contribution of quality

[1] See Figure E.1 and further details and discussions about this fact in Appendix E.1.

[2] 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). A related problem is one of changing consumer tastes for products and how it should affect our aggregate indices for price or real economic outcomes (Redding and Weinstein, 2020; Baqaee and Burstein, 2022).

change to the aggregate price index of US imports. We show that access to better quality products is the primary source of consumption gains from the rise in import 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 the standard imports price index, we substantially raise the estimates of consumption gains from US imports over this period.

The estimates of price elasticities play a key role in determining both the inferred changes in quality and the value of new varieties to consumers. Our approach to the identification of demand allows us to consider a wide class of homothetic demand systems featuring heterogeneous price elasticities, and to allow for correlated shocks to marginal costs and demand. We thus improve upon the standard approach for estimating price elasticities in trade data (Feenstra, 1994), which assumes constant elasticities (CES demand) and imposes uncorrelated product-level supply and demand shocks. The latter assumption is untenable if we associate demand shocks with quality.

The idea of our approach is to apply the dynamic panel (DP) methods to the joint evolution of product-level prices and demand (quality) shocks. More specifically, we assume shocks to the current demand (quality) of each product that, conditional on lagged product demand (quality), are uncorrelated with lagged product prices.[3] This assumption is trivially satisfied if we rule out dynamic pricing (e.g., when prices are flexible and demand does not directly depend on past prices). Alternatively, even under dynamic pricing, this assumption is still satisfied if current demand shocks are outside the information set of the firms when they choose their prices in past periods. Under either scenario, we can derive moment conditions that identify flexible demand systems in the presence of correlated supply and demand shocks. The only additional requirement is that product prices exhibit strong autocorrelation over time.

Since our identification allows us to estimate flexible demand systems, we also provide a theoretical characterization of the changes in the aggregate price index for a broad family of homothetic demand systems. Our results further decompose these changes into the contributions of changes in price, quality, and the available set of products (product entry/exit). The family of demand systems considered here is characterized by up to two distinct aggregate indices and nests the three homothetic demand systems presented by Matsuyama and Ushchev (2017) (see, also Matsuyama, 2022). Thus, our results generalize

[3]This strategy has been combined with complementary instrumental variables in estimating rich demand systems in several IO applications (e.g., Grennan, 2013; Lee, 2013; Sweeting, 2013), and in estimating firm-level production functions (Caliendo et al., 2020). We note that our assumptions about the dynamics of demand shocks are also in line with Redding and Weinstein (2020), who find a strong persistence in demand shocks in the Nielsen barcode data.

the widely used Feenstra (1994) variety correction and the unified price index (CUPI) of Redding and Weinstein (2020) from CES to a wide class of homothetic demand systems.[4]

Before applying our method to the customs data, we validate it in the well studied context of data on the US automobile market (1980-2018). In this setting, we have detailed product characteristics, including horsepower, miles-per-dollar, and space, that we can use as proxies for product quality. We show that, controlling for lagged product characteristics, current product characteristics are not correlated with lagged prices. This result provides direct evidence in favor of our main identification assumption.

Using the auto data, we further compare our identification strategy against a standard cost shock instrument based on the real exchange rate (RER) between each car's country of assembly and the US. We find similar demand estimates using the two identification strategies, both for CES demand and for Kimball (1995) demand, which is a homothetic demand system with variable elasticities nested within the family considered in our theory. Moreover, we show that our estimated Kimball demand system leads to own-price elasticities that are higher than those of CES, but closely in line with those found based on a random coefficients logit model (BLP) (Berry, 1994; Berry et al., 1995). The latter is the benchmark demand model commonly used in settings with available data on product characteristics. Lastly, we examine our inferred measures of quality and show that they are correlated with characteristics valued by consumers.

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 express import prices relative to the US consumer price index (CPI). We then create a basket of OECD countries as our benchmark for quality, assuming that the quality of the varieties produced by these countries on average evolves similarly to that of products covered by the CPI in the US. This allows us to express the quality of the varieties supplied by all other countries relative to this baseline set of products.

In the case of Kimball demand (featuring variable price elasticities), 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 responsible for a cumulative decline of about 17% (0.95% annually). 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% cu-

[4]For another generalization of the Feenstra variety correction to alternative family of demand systems, and its application to the cereal market in the US, see Foley (2021).

mulative drop in the aggregate index of import prices.[5] 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 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.

Prior Work Our paper is related to the literature that attempts to measure the welfare gains from trade liberalization.[6] 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).[7] 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.

The role of product quality for the patterns of international trade and specialization, at the aggregate and at the firm level, has been the subject of a vast body of theoretical and empirical work (e.g., Linder, 1961, Flam and Helpman, 1987; Hummels and Skiba, 2004; Hallak, 2006; Verhoogen, 2008; Fajgelbaum et al., 2011; Baldwin and Harrigan, 2011; Kugler and Verhoogen, 2012; Manova and Zhang, 2012; Martin and Mejean, 2014; Dingel, 2017; Eaton and Fieler, 2022). Early empirical work on the importance of quality proxied

[5]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.

[6]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).

[7]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).

product quality with unit values (e.g., Schott, 2004; Hummels and Klenow, 2005).[8] As already mentioned, we follow the approach pioneered by Khandelwal (2010) and Hallak and Schott (2011) in attributing higher quality to products with higher demand, conditional on price.

Our paper is closely related to Feenstra and Romalis (2014), who offer a comprehensive attempt as measuring quality in trade flows across many different countries. Unlike our approach, they impose parametric restrictions on the relationship between quality and income elasticity, on the production cost of quality, and on the distribution of product quality in order to construct their quality measures. Our paper is also closely related to the recent paper by Redding and Weinstein (2021), who decompose the different margins of change in US imports, using a detailed nested CES structure that additionally accounts for firm heterogeneity. Relative to these studies, our contribution is to offer a novel identification strategy that only requires assumptions on the dynamics of demand shocks and, crucially, generalizes beyond CES demand to allow for heterogeneous elasticities.[9]

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; Baqaee and Burstein, 2022).[10] 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 apply 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 and HSA demand to study variable markups and pass-through (e.g., Amiti et al., 2019, Baqaee and Farhi, 2020, Wang and Werning, 2020, Matsuyama and Ushchev,

[8]Several studies have relied on measures of quality available for specific sets of products (e.g., wine as in Crozet et al., 2012), or as narrower proxies such as the ISO 9000 management scores (e.g., Verhoogen, 2008).

[9]In a recent study, Head and Mayer (2021) study counterfactual trade policy exercises in a models with CES and with BLP, in the context of the original automobile market dataset of Berry et al. (1995). While they find similar results, they emphasize the importance of incorporating heterogeneity in pass-throughs through oligopolistic competition under the CES model.

[10]In addition to changes in taste, the dependence of demand on income (nonhomotheticity) also matters for the measurement of consumption gains. Here, we abstract from this consideration by focusing on homothetic demand. Jaravel and Lashkari (2021) provide a method for tackling this problem based on cross-sectional consumption data.

2022).[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 such demand systems using data on observed prices and market shares.[12]

The paper is organized as follow. Section 2 presents the homothetic demand systems we consider, our approach to their identification, and our theoretical results on the change in their aggregate price index. 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 data on prices and market shares (or quantities) of different products or varieties (we use the two terms interchangeably) in a given market. We observe the sequence $(\boldsymbol{s}_t)_{t=0}^{T-1}$ where $\boldsymbol{s} \equiv (s_i)_{i \in V}$ stands for the vector of market shares chosen by the consumer(s) in a set V of products. At time t, a set V_t of products has nonzero market shares (so that $s_{it} = 0$, $i \notin V_t$). We additionally observe the sequence $(\boldsymbol{p}_t)_{t=0}^{T-1}$ where $\boldsymbol{p} \equiv (p_i)_{i \in V_t}$ stands for the vector of prices faced by the consumer(s) in the set V_t of available products. With slight abuse of notation, we also use the notation $\boldsymbol{s} \equiv (s_i)_{i \in V_t}$, where $\boldsymbol{s}$ may alternatively refer to the vector of expenditure shares limited to the set of available products V_t.

Our goal is to characterize the welfare changes of consumers due to changes in the set of available products V_t, changes in the prices of these products, or changes in their (unobserved) qualities. Crucially, we assume no additional information on the characteristics of the products or the underlying production costs. We proceed in three steps. We first state our assumptions regarding the structure of the underlying demand system that rationalizes the observed prices and market shares in Section 2.1. We then present our Dynamic Panel (DP) approach to the estimation of demand in Section 2.2. We finally present our characterization of the change in the aggregate price index in the entire market in Section 2.3.

[11] For instance, allowing for variable markups, 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. Since we use aggregate trade data, we cannot directly speak to this margin. However, when we apply our method at the firm-level, we can provide measures of markups based on our estimated price elasticities. In our application to the US auto market, we show that our estimated markups are in line with those found by Grieco et al. (2021) using BLP demand.

[12] For an alternative approach to the estimation of HSA demand, see Kasahara and Sugita (2021).

2.1 Homothetic Demand with Variable Elasticities of Substitution

We consider homothetic demand systems that are rationalizable by a well-defined underlying utility function, which, without loss of generality, we can characterize as follows.

Definition 1 (*Homothetic Demand System*)**.** A homothetic demand system parameterized by a vector of parameters $\varsigma \in \mathbb{R}^D$ can be characterized by a collection of expenditure-share functions $\mathcal{S}_i(\cdot;\varsigma)$, satisfying $\sum_{i\in V}\mathcal{S}_i(\widetilde{\boldsymbol{p}};\varsigma) \equiv 1$ for all $\widetilde{\boldsymbol{p}}$ and V, and a linear homogeneous aggregator $\mathcal{H}(\cdot;\varsigma)$, satisfying $\mathcal{H}(\alpha\boldsymbol{p};\varsigma) = \alpha\mathcal{H}(\boldsymbol{p};\varsigma)$ for all $\boldsymbol{p}$, V, and $\alpha > 0$, such that the expenditure share of product $i \in V$ under prices $\boldsymbol{p}$ is given by $\mathcal{S}_i\left(\frac{\boldsymbol{p}}{\mathcal{H}(\boldsymbol{p};\varsigma)};\varsigma\right)$.

Note that the only constraint implied by Definition 1 is the homotheticity of the underlying preferences, since the composition of demand only depends on the relative prices across products (and not on the total consumer expenditure and/or the average level of prices). At this point, the introduction of the aggregator index $\mathcal{H}(\cdot;\varsigma)$ is not strictly necessary; it explicitly ensures that the composition of demand does not depend on the level of prices, since multiplying all prices by a factor $\alpha > 0$ leaves the composition of demand intact. For this reason, we will rely on this explicit index in the inversion of the demand system in the estimation. Appendix A.1 presents the choices of expenditure-share and aggregator functions that lead to alternative demand systems such as mixed logit demand, homothetic AIDS and Translog, and the HSA demand system of Matsuyama and Ushchev (2017).

To characterize a general homothetic demand system following Definition 1, we need to specify a $|V|$-dimensional vector of expenditure-share functions $\boldsymbol{\mathcal{S}}(\cdot;\varsigma) \equiv (\mathcal{S}_i(\cdot;\varsigma))_{i\in V}$, in the space of $|V|$-dimensional price vectors. The dimensionality of the corresponding space of cross-product elasticities of substitution grows quadratically in the size of the product space $|V|$. Given that the number of observations grows proportionally to $|V| \times T$, it is not feasible to estimate a demand system that is fully parameterized in this space, unless if we have access to a long panel (such that $|V| \ll T$).[13]

A common alternative is to summarize the patterns of cross-product elasticities of substitution as a function of one or two aggregate indices of all available products. The following definition specializes the general homothetic demand system of Definition 1 to a broad family of demand systems that use up to two such indices.

[13] If we have access to information on a vector of product characteristics $\boldsymbol{x}_i$ for each product i, we can still express rich patterns of cross-product elasticities of substitution in the space of product characteristics, whose dimensionality does not grow with the number of products $|V|$. For instance, the mixed logit demand system (McFadden, 1974; Berry, 1994) relies on product characteristics to define the expenditure-share functions as $\mathcal{S}_i(\boldsymbol{p};\varsigma) \equiv \int \frac{\exp(-\sigma \log p_i + \boldsymbol{\beta}'\boldsymbol{x}_i)}{\sum_{i'\in V}\exp\left(-\sigma \log p_{i'} + \boldsymbol{\beta}'\boldsymbol{x}_{i'}\right)} dF(\sigma,\boldsymbol{\beta};\varsigma)$

Definition 2 (*Homothetic with Aggregator Demand System*)**.** Consider the homothetic demand system of Definition 1 for a linear homogenous aggregator function $\mathcal{H}(\cdot;\varsigma)$ and the expenditure-share functions $\mathcal{S}_i(\cdot;\varsigma)$ that satisfy

$$\mathcal{S}_i(\widetilde{\boldsymbol{p}};\varsigma) \equiv \frac{\widetilde{p}_i \mathcal{D}_i(\widetilde{p}_i;\varsigma)}{\sum_{i' \in V} \widetilde{p}_{i'} \mathcal{D}_{i'}(\widetilde{p}_{i'};\varsigma)}, \tag{1}$$

for a collection of single-argument demand functions $\mathcal{D}_i(\cdot;\varsigma)$ that are positive-valued and decreasing over some interval $\widetilde{p} \in \left(0, \underline{\widetilde{p}}_i\right)$ and satisfy $\lim_{\widetilde{p}_i \to \underline{\widetilde{p}}_i} \mathcal{D}_i(\widetilde{p}_i;\varsigma) = 0$ and $\mathcal{D}_i(\widetilde{p}_i;\varsigma) = 0$ for $\widetilde{p} \geq \underline{\widetilde{p}}_i$ where $\underline{\widetilde{p}}_i \in \mathbb{R}_+ \cup \{\infty\}$.

We refer to the demand system in Definition 2 as homothetic with aggregator (HA) since we can characterize them using two aggregate indices $H \equiv \mathcal{H}(\boldsymbol{p};\varsigma)$ and $A \equiv \sum_{i'} \frac{p_{i'}}{H} \mathcal{D}_{i'}\left(\frac{p_{i'}}{H};\varsigma\right)$ as $s_i \equiv \frac{p_i}{A\,H}\mathcal{D}_i\left(\frac{p_i}{H};\varsigma\right)$. The demand function $\mathcal{D}_i(\cdot;\varsigma)$ for product i only depends on the price of product i relative to the aggregate index H that summarizes the effects of the prices of all other products on the demand for product i. This restriction substantially reduces the potential dimensionality of the parameter space.

For each product i, Definition 2 also defines a constant *relative choke price* $\underline{\widetilde{p}}_i$, as the value of quality-adjusted relative price for which the demand falls to zero. For instance, for the CES demand systems, the demand elasticity function is a constant and the relative choke price is infinity ($\underline{\widetilde{p}}_i \equiv \infty$). More generally, however, consumer demand may fall to zero for finite values of prices.

Definition 2 nests many well-known homothetic demand systems commonly used in the literature, but does not ensure that they are rationalized by an underlying utility function. The following definition characterizes the rationalizable homothetic demand systems recently introduced by Matsuyama and Ushchev (2017) (see also Matsuyama, 2022), which are all nested in HA demand.

Definition 3. The following families of demand HA demand are rationalizable.

1. *Homothetic with a Single Aggregator (HSA)*. This system is characterized by an aggregator function $\mathcal{H}(\cdot;\varsigma) \equiv H$ that is implicitly defined by the value of H that satisfies $1 = \sum_{i \in V} \frac{p_i}{H}\mathcal{D}_i\left(\frac{p_i}{H};\varsigma\right)$.

2. *Homothetic Implicit Additive (HIA).* This system is characterized by an aggregator function $\mathcal{H}(\cdot;\varsigma) \equiv H$ that is implicitly defined by the value of H that, depending

on the type of HIA demand, satisfies one of the two following conditions

$$1 = \begin{cases} \sum_{i \in V} \int_0^{\mathcal{D}_i\left(\frac{p_i}{H};\varsigma\right)} \mathcal{D}_i^{-1}(v;\varsigma)\, dv, & \text{directly additive type,} \\ \sum_{i \in V} \int_0^{\frac{p_i}{H}} \mathcal{D}_i(v;\varsigma)\, dv, & \text{indirectly additive type,} \end{cases} \tag{2}$$

where each condition corresponds to one of the two types of HIA demand: directly or indirectly additive.

The homothetic implicitly additive (HIA) systems requires two distinct aggregate indies H and A to characterize demand. In contrast, the homothetic single aggregator (HSA) system is completely characterized using the aggregate index H, and we always have $A \equiv 1$. As shown by Matsuyama and Ushchev (2017), the only demand system that belongs to both HIA and HSA families is the CES demand system, which corresponds to the choice of expenditure-share function $\mathcal{S}_i(\widetilde{\boldsymbol{p}};\varsigma) \equiv \widetilde{p}_i^{1-\sigma}$ and aggregator function $\mathcal{H}(\boldsymbol{p};\varsigma) \equiv \sum_i p_i^{1-\sigma}$ where $\varsigma \equiv (\sigma)$.

In our empirical exercise, we will particularly focus on a special case of the HIA demand, the Kimball demand system, which assumes identical demand functions $\mathcal{D}_i(\cdot;\varsigma) \equiv \mathcal{D}(\cdot;\varsigma)$ across products and implicitly defines the aggregator function $\mathcal{H}(\cdot;\varsigma)$ as the directly additive case in Equation (2). In this specification, the space of parameters remains constant and does not change in the number of available products $|V|$.

Demand/Quality Shocks For a general, parametric family of homothetic demand systems given by Definition 1, we can assume that the observed sequence of prices and expenditure shares satisfy

$$s_{it} = \mathcal{S}_i\left(\frac{\left(e^{-\varphi_{it}} p_{it}\right)_{i \in V_t}}{\mathcal{H}\left(\left(e^{-\varphi_{it}} p_{it}\right)_{i \in V_t};\varsigma\right)};\varsigma\right), \tag{3}$$

where $\left(e^{-\varphi_{it}} p_{it}\right)_{i \in V_t}$ denotes the vector of prices for all products i at time t adjusted by the structural error φ_{it}. The specification in Equation (4) implies that the higher the demand shock φ_{it} for a product with a fixed level of price, the higher the consumer demand will be for the product. Generally, we may interpret φ_{it} as an unobserved demand shock to the quality or appeal of product i at time t. In what follows, we consider cases where we may interpret the variations in this residual demand as being driven by changes in unobserved characteristics $\boldsymbol{x}_{it}$ of products over time and thus refer to it as quality.[14] For

[14]For instance, if we define a product at the level of barcodes in standard scanner data, in which product characteristics $\boldsymbol{x}_i$ for product i remain constant over time, it is more reasonable to assume that demand

instance, we may assume that $\varphi_{it} \equiv \boldsymbol{\beta}'\boldsymbol{x}_{it} + \psi_{it}$ where $\boldsymbol{\beta}$ is a vector specifying the value of each characteristic for consumers.

Note that a constant shift in all demand shock parameters φ_{it} keeps the demand unchanged. We therefore normalize the demand shocks by assuming that there exists a set of base products $O \subset V_t$, for all t, whose quality remains on average constant throughout the entire period, implying $\sum_{o \in O} \varphi_{ot} = 0$. Therefore, we interpret φ_{it} as the (unobserved) quality of i relative to the average base product.

2.2 The Dynamic Panel Approach to Demand Estimation

In this section, we consider identifying a parametrized homothetic demand system, as characterized by Definition 1, where data on expenditure shares and prices are assumed to follow Equation (3). Let us define the quality-adjusted relative price of product i at time t as

$$\widetilde{p}_{it} \equiv \frac{e^{-\varphi_{it}} p_{it}}{H_t}, \qquad H_t \equiv \mathcal{H}\left(\left(e^{-\varphi_{it}} p_{it}\right)_{i \in V_t}; \varsigma \right). \tag{4}$$

Note that the space of the quality-adjusted relative price vectors $\widetilde{\boldsymbol{p}}_{it}$ at time t constitutes a $(|V_t| - 1)$- dimensional manifold in $\mathbb{R}^{|V_t|}$ since all such vectors satisfy $\mathcal{H}\left(\widetilde{\boldsymbol{p}}_{it}\right) = 1$. We now assume that the demand system satisfies the connected substitutes property of Berry et al. (2013), and is thus a bijection from the space of quality-adjusted relative prices to the space of consumption expenditure shares. As a result, there exists an inverted demand function $\boldsymbol{\pi}\left(\cdot; \varsigma\right)$ such that we have $\widetilde{p}_{it} = \pi_i\left(\boldsymbol{s}_t; \varsigma\right)$.

Let $\langle v_{it} \rangle \equiv \frac{1}{|O|} \sum_{i \in O} v_{it}$ denote the unweighted mean of variable v_{it} within the set of base products O, where $|O|$ is the size of this set. Using Equation (4) and the normalization of quality in the set of base products, we can then write quality shocks as a function of observed expenditure shares and prices according to[15]

$$\varphi_{it} = \log \widehat{p}_{it} - \log \widehat{\pi}_i\left(\boldsymbol{s}_t; \varsigma\right), \qquad i \in V_t. \tag{5}$$

where we have defined the notation where $\log \widehat{v}_{it} \equiv \log v_{it} - \langle \log v_{it} \rangle$ denotes the difference between the logarithm of variable $v_{i,t}$ and its unweighted mean within the set of

shocks are driven by changes in product appeal (consumer taste) (e.g., Redding and Weinstein, 2020). In the settings considered in this paper, 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 unobserved changes in the set of varieties within each product classification code that is available to consumers.

[15] By definition, we have $\log p_{it} - \log h_t - \varphi_{it} = \log \pi_i\left(\boldsymbol{s}_t; \varsigma\right)$. Using the condition $\frac{1}{|O|} \sum_{o \in O} \varphi_{ot} = 0$ then leads to Equation (5).

base products.

Equation (5) 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.

2.2.1 Identification Assumptions

We begin by imposing the following restrictions on the stochastic dynamics of the quality shocks.

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

$$\varphi_{it} = g_i\left(\varphi_{it-1}; \boldsymbol{\varrho}\right) + u_{it}, \tag{6}$$

where u_{it} is a zero-mean i.i.d innovation to the demand shock and where $\boldsymbol{\varrho}$ is a vector of parameters characterizing the persistence of the demand shock process.[16]

Equation (6) implies that despite potential persistence in the process of quality shocks, these shocks cannot be completely predicted based on past realizations due to the arrival of innovations in each period. In our baseline model, we assume that the demand shock process is a stationary AR(1) process with a product-specific mean:[17]

$$g_i\left(\varphi_{it-1}; \boldsymbol{\varrho}\right) \equiv \rho\varphi_{it-1} + (1-\rho)\,\phi_i, \tag{7}$$

where $\boldsymbol{\varrho} \equiv (\rho, \boldsymbol{\phi})$ is the vector of the parameters of the Markov process, and where ϕ_i constitutes the expected long-run mean quality of product i.

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)**.** *Demand shock innovations are zero mean, conditional on lagged log prices (and potentially the latter's powers):*

$$\mathbb{E}\left[u_{it} \middle| \left(\log p_{it-1}\right)^m\right] = 0, \qquad 1 \leq m \leq D, \tag{8}$$

[16] 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.

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

where $D \geq 1$ denotes the dimensionality of the parameters characterizing consumer demand. Moreover, we assume that the log price process has a nonzero autocorrelation $\mathbb{E}\left[\log p_{it-1} \log p_{it}\right] \neq 0$.

In combination with Equations (5) and (6), we can use Equation (8) to derive a number of orthogonality conditions that allow us to estimate the vectors of parameters $\boldsymbol{\varsigma}$ and $\boldsymbol{\varrho}$, leading to the following moment conditions

$$\mathbb{E}\left[\left(\log \widehat{p}_{i,t} - \log \widehat{\pi}_i\left(\boldsymbol{s}_t; \boldsymbol{\varsigma}\right) - g_i\left(\log \widehat{p}_{i,t-1} - \log \widehat{\pi}_i\left(\boldsymbol{s}_{t-1}; \boldsymbol{\varsigma}\right); \boldsymbol{\varrho}\right)\right) \times z_{it-1}\right] = 0, \tag{9}$$

where z_{it} is an instrument that is orthogonal to the value of the quality innovation u_{it} for product i at time t, given by the expression within the main parentheses. The instruments z_{it} include lagged values of different powers of log prices $\left(\log p_{it-1}\right)^m$ for $m \leq D$, a combination of lagged value of the quality shock φ_{it-1} (and potentially its powers) given by Equation (5), and product dummies, depending on the structure of the process $g_i\left(\cdot; \boldsymbol{\varrho}\right)$. For instance, in the case of AR(1) process considered in Equation (7), we use the lagged quality shocks φ_{it-1} and product dummies to identify ρ and ϕ_i's. The assumption of nonzero autocorrelation ensures that the lagged values of log prices offer meaningful instruments for the corresponding contemporaneous values of the same variables.

Example: CES Demand As an example, let us consider the case of CES demand where, as already mentioned, we have $\mathcal{S}_i\left(\widetilde{\boldsymbol{p}}; \boldsymbol{\varsigma}\right) \equiv \widetilde{p}_i^{1-\sigma}$, $\mathcal{H}\left(\boldsymbol{p}; \boldsymbol{\varsigma}\right) \equiv \sum_i p_i^{1-\sigma}$, and where $\boldsymbol{\varsigma} \equiv (\sigma)$. Here, we can analytically write the inverse demand function $\pi_i\left(\boldsymbol{s}; \sigma\right) \equiv s_i^{1/(1-\sigma)}$. From Equation (5), we can write the quality shock as $\varphi_{it} = \log \widehat{p}_{it} + \frac{1}{\sigma-1} \log \widehat{s}_{it}$. Since a single parameter σ fully characterizes demand, we only need to use the case of $D = 1$ in Equation (8), and thus use the orthogonality conditions $\mathbb{E}\left[u_{it} | \log p_{it-1}\right] = 0$, $\mathbb{E}\left[u_{it} | \varphi_{it-1}\right] = 0$, $\mathbb{E}\left[u_{it} | \varphi_{it-1}\right] = 0$, and $\mathbb{E}\left[u_{it}\right] = 0$ for each product i and each time t.

If we further consider the AR(1) assumption in Equation (7), we can leverage the log-linearity of the model and write the moment conditions in first-differences as

$$\mathbb{E}\left[\left(\Delta \log \widehat{p}_{it} + \frac{1}{\sigma - 1} \log \widehat{s}_{it} - \rho\left(\Delta \log \widehat{p}_{it-1} + \frac{1}{\sigma - 1} \log \widehat{s}_{it-1}\right)\right) \times z_{it}\right] = 0, \tag{10}$$

where $\Delta \log v_{it} \equiv \log v_{it} - \log v_{it-1}$ for any variable v_{it}, and the instruments z_{it} include *double* lagged log prices and demand shocks, in addition to the time and product dummies, corresponding to the case of $D = 1$ in Equation (8). In this case, we can identify the demand elasticity parameter σ and the demand shock persistence ρ without the need to estimating the long-run mean of product-level demand shocks ϕ in Equation (7).

2.2.2 Discussion

The Logic of Identification To gain more intuition about the assumption in Equation (8), we present 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, letting q_{it} denote the quantity of product i purchased by consumers, this scenario leads to the following process for the evolution of log prices:

$$\log p_{it} = \log mc_i \left(q_{it}, \varphi_{it}, w_{it}\right) + \log \mu_i \left(\boldsymbol{p}_t, \boldsymbol{s}_t, \boldsymbol{\varphi}_t\right) + v_{it}, \tag{11}$$

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 markup function, which may depend on the vector of current prices $\boldsymbol{p}_t$, market shares $\boldsymbol{s}_t$, 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 (11) satisfies Equation (8) even if the firm knows its future demand shock innovation.[18]

More generally, we may consider a model of dynamic price setting in which the log price additionally depends on 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 (8). 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 exogenous cost shifters w_{it}, which affect prices through marginal cost as in Equation (11), as instruments to estimate Equation (5). As already mentioned, we are interested in settings where we only have access to information on

[18]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.

prices and quantities. Our identification assumption allows us to use the lagged values of log price as an instrument for current log 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 instruments is that of Feenstra (1994), which 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 (11), 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.4 in Appendix B 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).

2.3 Accounting for Consumption Gains

Since we consider homothetic preferences, we can define a price index (unit expenditure function) P_t that summarizes the effect of the set of available products, their prices, and their quality at time t for the welfare of the consumer(s) into a single number. In this section, we provide a characterization of the change in the price index that accounts for the contributions of each of the three channels (set of available products, prices, and quality).

For the results of this section, we limit our attention to the family of homothetic with aggregator (HA) demand systems specified in Definition 2. Under this family of demand systems, we can define a demand elasticity as a function of quality-adjusted relative price for each product i as

$$\sigma_i\left(\widetilde{p}\right) \equiv -\frac{\widetilde{p}\,\mathcal{D}_i'\left(\widetilde{p}\right)}{\mathcal{D}_i\left(\widetilde{p}\right)}, \tag{12}$$

where we have suppressed the dependence on the parameter vector ς to simplify the expression. Assuming that the observed data satisfies Equation (3), we let $\sigma_{it} \equiv \sigma_i\left(e^{-\varphi_{it}} p_{it}/H_t\right)$ denote the demand elasticity for product i at time t, and denote the corresponding love-of-variety parameter as $\mu_{it} \equiv \frac{1}{\sigma_{it}-1}$.

2.3.1 Exact Measurement of Consumption Gains

Consider the changes in the set of products, prices, and qualities faced by consumers in the market between periods $t-1$ and t. Define the *common set* $V_t^* \equiv V_{t-1} \cap V_t$ to be the set of products common between the two periods. We now assume some smooth paths of prices and qualities $(\boldsymbol{p}_\tau, \boldsymbol{\varphi}_\tau)$ in the interval $\tau \in (t-1, t)$ that in either end of the interval approach the values of prices and qualities in periods $t-1$ and t. Formally, we assume these paths satisfy $\lim_{\tau \to t-1} (p_{i\tau}, \varphi_{i\tau}) = (p_{it-1}, \varphi_{it-1})$ for $i \in V_{t-1}$, $\lim_{\tau \to t} (p_{i\tau}, \varphi_{i\tau}) = (p_{it}, \varphi_{it})$ for $i \in V_t$, and

$$\lim_{\tau \to t-1} e^{-\varphi_{i\tau}} p_{i\tau} = H_{t-1}\, \underline{\widetilde{p}}_i \quad \text{for } i \in V_t \backslash V_t^*, \qquad \lim_{\tau \to t} e^{-\varphi_{i\tau}} p_{i\tau} = H_t\, \underline{\widetilde{p}}_i \quad \text{for } i \in V_{t-1} \backslash V_t^*. \tag{13}$$

Importantly, Equation (13) implies that the quality-adjusted relative price of the products that are unavailable in each period approach their corresponding relative choke prices.

Along the paths above, we can apply the definition of the demand system in Equation (3) to define the corresponding paths of expenditure shares $s_{i\tau}$, the aggregate indices H_τ and A_τ, and demand elasticities and love-of-variety parameters $\sigma_{i\tau}$ and $\mu_{i\tau}$. We also define the total expenditure share of the common set as $\Lambda_\tau^* \equiv \sum_{i \in V_t^*} s_{i\tau}$ and the expenditure shares within the common set as $s_{i\tau}^* \equiv s_{i\tau}/\Lambda_\tau^*$ for $i \in V_t^*$. Correspondingly, we also define the expenditure-share weighted mean of any product-specific variable $v_{i\tau}$ within the common set as $\overline{v}_\tau^* \equiv \sum_{i \in V_t^*} s_{i\tau}^* v_{i\tau}$.

Our first result characterizes the change in the price index for any well-defined homothetic with aggregator (HA) demand system along the paths of prices, qualities, and expenditure shares constructed above.

Proposition 1. *The relative change in the price index of an HA demand, specified in Definition 2, at any point on the interval $\tau \in (t-1, t)$ satisfies*

$$\begin{aligned} d\log P_\tau &= d\log D_\tau^* - d\log \Phi_\tau^* \\ &\quad + \overline{\mu}_\tau^*\, d\log \Lambda_\tau^* + (\overline{\mu}_\tau^* - \overline{\mu}_\tau)\, d\log A_\tau + \sum_{i \in V_t^*} \mu_{i\tau} ds_{i\tau}^* - \sum_{i \in V_{t-1} \cup V_t} \mu_{i\tau} ds_{i\tau}, \end{aligned} \tag{14}$$

where we have defined the Divisia price and quality indices $d\log D_\tau^*$ and $d\log \Phi_\tau^*$ within the common set as

$$d\log D_\tau^* \equiv \sum_{i \in V_t^*} s_{i\tau}^* d\log p_{i\tau}, \qquad d\log \Phi_\tau^* \equiv \sum_{i \in V_t^*} s_{i\tau}^* d\varphi_{i\tau}. \tag{15}$$

Moreover, based on the normalization of quality in the set O of base products, we can also write *this change in terms of changes in prices, expenditure shares, and the A_τ aggregator index, as well as the demand elasticities of each product as*

$$d\log P_\tau = \langle d\log p_{it}\rangle + \langle \mu_{it} d\log s^*_{it}\rangle + \langle \mu_{it}\rangle\, d\log \Lambda^*_\tau + (\langle \mu_{it}\rangle - \overline{\mu}_\tau)\, d\log A_\tau - \sum_{i\in V_{t-1}\cup V_t} \mu_{i\tau} ds_{i\tau}, \tag{16}$$

where, as before, $\langle v_{it}\rangle \equiv \frac{1}{|O|}\sum_{i\in O} v_{it}$ denotes the unweighted mean of variable v_{it} within the set of base products.

Proof. See Appendix B.1. □

Equation (14) expresses the growth in the price index at any point along the path as the sum of three main contributions: the first and the second terms account for the changes in the prices and qualities of the continuing products within the common set. The remaining terms on the second line account for the changes in the sets of entering and exiting products.

To unpack this result, let us first consider the special case of the CES demand system where, as we saw, we have $A_\tau \equiv 1$, $\sigma_{i\tau} \equiv \sigma$ and $\mu_{i\tau} \equiv \frac{1}{\sigma-1}$. As a result, Equations (14) and (16) simplify to

$$d\log P_\tau = d\log D^*_\tau - d\log \Phi^*_\tau + \tfrac{1}{\sigma-1}\, d\log \Lambda^*_\tau, \tag{17}$$

$$= \langle d\log p_{it}\rangle + \tfrac{1}{\sigma-1}\langle d\log s^*_{it}\rangle + \tfrac{1}{\sigma-1}\, d\log \Lambda^*_\tau. \tag{18}$$

The three terms in the first equation account for the contributions of the change in price, quality, and product entry/exit. Since the means in the set of base products are unweighted, we can explicitly integrate Equation (18) to find the following exact result for the change in the CES price index:[19]

$$\Delta\log P_t = \langle \Delta\log p_{it}\rangle + \tfrac{1}{\sigma-1}\langle \Delta\log s^*_{it}\rangle + \frac{1}{\sigma-1}\Delta\log \Lambda^*_\tau. \tag{20}$$

Consider the case where we assume that the set of base products corresponds to the current set, $O \equiv V_t$. In this case, Equation (20) corresponds to the logarithm of the CES

[19] Integrating Equation (17), we also find the following exact decomposition of the change in the CES price index to changes in price, quality, and the set of available products (Redding and Weinstein, 2020):

$$\Delta\log P_t = \sum_{i\in V^*_t} \tilde{s}^*_{it}\Delta\log p_{it} + \sum_{i\in V^*_t} \tilde{s}^*_{it}\Delta\varphi_{it} + \tfrac{1}{\sigma-1}\, d\log \Lambda^*_\tau, \tag{19}$$

where $\tilde{s}^*_{it} \propto \Delta s^*_{it}/\Delta\log s^*_{it}$ are the Sato-Vartia weights defined in the common set, satisfying $\sum_{i\in V^*_t}\tilde{s}^*_{it} = 1$.

unified price index (CUPI) defined by Redding and Weinstein (2020): the first term is the logarithm of the Jevons index within the common set, the second term is the logarithm of the geometric mean of the relative change in the expenditure shares within the common set, and the last term is the standard Feenstra (1994) CES correction for the contributions of product entry/exit.

Once we deviate from the CES assumption, Equations (14) and (16) show how the heterogeneity in the demand elasticities σ_{it} affect the change in the unit expenditure function P_τ. First, comparing Equations (14) and (17), we find that in the presence of heterogeneity in demand elasticities, the contribution of product entry and exit to the change in the price index is given by

$$\underbrace{\overline{\mu}_\tau^* \, d\log\Lambda_\tau^*}_{\text{generalized Feenstra correction}} + \underbrace{(\overline{\mu}_\tau^* - \overline{\mu}_\tau)\, d\log A_\tau}_{\text{love-of-variety gap}} + \underbrace{\left(\sum_{i\in V_t^*} \mu_{i\tau} ds_{i\tau}^* - \sum_{i\in V} \mu_{i\tau} ds_{i\tau}\right)}_{\text{love-of-variety reallocation}}.$$

The first term above generalizes the Feenstra (1994) CES variety correction to the case with heterogeneous demand elasticities. In this case, the relevant love-of-variety index is the weighted mean $\overline{\mu}_\tau^*$ of love-of-variety parameters within the common set. The second term accounts for the gap between the mean love-of-variety index within the common set and across all products. The third term shows that we need to additionally account for the effects of the reallocations of consumer expenditure across products that have different degrees of substitutability for consumers. More specifically, this term corresponds to the gap between these reallocations across the set of all products and those within the common set. If reallocations toward products with higher love of variety are stronger outside relative to inside the common set, this expression predicts a lower change in the price index than what is predicted by the Feenstra (1994) CES variety correction.

Equations (14) and (16) expressed in terms of the change in the aggregate index A_τ. We can further simplify these expressions by removing this term for the HSA and HIA demand systems of Definition 3. In the case of HSA, we have that $A_t \equiv 1$. In the HIA case, we can show that the unit expenditure function is given by the product of the two aggregate indices:

$$P_\tau = H_\tau \, A_\tau. \tag{21}$$

Using these observations, the following lemma characterizes the change in the aggregate index A_τ as a function of the love-of-variety weighted change in the market shares of different products. Using this lemma allows us to expressed the change in the unit expenditure function only as a function of changes in prices and expenditure shares, and the demand elasticities.

Lemma 1. *For the HSA and HIA demand systems of Definition 3, the change in the price index satisfies*

$$d\log A_t = \begin{cases} 0, & HSA, \\ -\frac{1}{1+\overline{\mu}_t}\sum_{i\in V}\mu_{it}ds_{it}, & HIA. \end{cases} \tag{22}$$

Proof. See Appendix B.1. □

Unlike the CES case, in the presence of heterogeneity in demand elasticities, we cannot exactly integrate the above results to construct the exact measures of change in the price index. We will instead construct second-order approximations for the change in the price index that we can compute in the data.

2.3.2 Approximate Measures of Consumption Gains

Since the paths that we constructed in Section 2.3.1 between periods $t-1$ and t in the limit approach the outcomes in those two periods, we can approximately integrate Equation (16) to find the change in the unit expenditure function between these two periods.

Define the Törnqvist average $\overline{\overline{v_{it}}} \equiv \frac{1}{2}\left(v_{it-1}+v_{it}\right)$ of variable v_{it} between periods $t-1$ and t. In particular, in computing $\overline{\overline{\mu}}_{it}$ for products that are outside the common set ($i \notin V_t^*$), we use the love of variety for product i at its relative choke price. For instance, for the products that enter between periods $t-1$ and t ($i \in V_t \backslash V_t^*$), we let $\overline{\overline{\mu_{it}}} \equiv \frac{1}{2}\left(\underline{\mu}_i + \mu_{it}\right)$ where $\underline{\mu}_i \equiv \lim_{\widetilde{p}\to\underline{\widetilde{p}}_i}\frac{1}{\sigma_i(\widetilde{p})-1}$. Using these definitions, the following lemma characterizes the change in the homothetic price index of any HA demand system up to the second order of approximation.

Lemma 2. *The relative change in the price index of any HA demand system, specified following Definition 2, between periods $t-1$ and t satisfies*

$$\Delta\log P_t = \sum_{i\in V_t^*}\overline{\overline{s_{it}^*}}\,\Delta\log p_{it} - \sum_{i\in V_t}\overline{\overline{s_{it}^*}}\,\Delta\varphi_{it} + \overline{\overline{\overline{\mu}_t^*}}\,\Delta\log\Lambda_t^*$$
$$+\overline{\overline{\left(\overline{\mu}_t^*-\overline{\mu}_t\right)}}\,\Delta\log A_t + \sum_{i\in V_t^*}\overline{\overline{\mu_{it}}}\,\Delta s_{it}^* - \sum_{i\in V}\overline{\overline{\mu_{it}}}\,\Delta s_{it}^* + O\left(\delta^3\right), \tag{23}$$

up to the second-order terms in $\delta \equiv \max\{\Delta\log\Lambda_t^*, \max_i\left|\Delta\log p_{it}\right|, \max_i\Delta\varphi_{it}\}$*, as* δ *approaches* *zero. Moreover, this relative change can also be written as*

$$\Delta \log P_t = \langle \Delta \log p_{it} \rangle + \langle \overline{\overline{\mu_{it}}}\, \Delta \log s^*_{it} \rangle + \overline{\overline{\langle \mu_{it} \rangle}}\, \Delta \log \Lambda^*_t + \overline{\overline{(\langle \mu_{it} \rangle - \overline{\mu}_t)}}\, \Delta \log A_t - \sum_{i \in V} \overline{\overline{\mu_{it}}}\, \Delta s_{it} + O\left(\delta^3\right), \tag{24}$$

Proof. See Appendix B.1 □

Equation (23) constitutes one of our main theoretical results. It provides a decomposition of the changes in the price index in a broad family of homothetic demand systems to the contributions of changes in prices, quality, and the set of available products. For any parameterized family of homothetic demand, applying our estimation scheme in Section 2.2 allows us to find the implied values of demand elasticity σ_{it} for each product i in the set of products V_t at time t and compute the index A_t. We can then apply Lemma 2 to compute the change in the price index between the two periods. Using the resulting estimates of quality change, we can also find the second-order approximation provided in Equation (23) for the decomposition of the change in the price index to the contributions of price change, quality change, and product entry/exit. Appendix A.2 uses the results of Lemma 1 to remove the need for computing the change in index A_t under the HSA/HIA demand families.

3 Validating the Strategy using US Auto Data

In this section, we apply the Dynamic Panel (DP) approach 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.[20] 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

[20]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).

an electric vehicle, a luxurious brand, or a new design (redesign), complement the data from the yearbooks.[21] 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.[22]

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 RER.[23] 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.

Before applying our methodology for demand estimation, we rely on the availability of product characteristics to directly test our identification assumption (Assumption 2). In Appendix C.2, we show that lagged log 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.

3.2 Empirical Demand Specification

In applying our framework to the auto data, we map each car model to a product/variety i in our data. For the specification of demand, we will rely on a particular parameterized family of HIA demand systems (Definition 3) commonly referred to as Kimball demand (Kimball, 1995). This specification corresponds to the directly additive HIA type, as specified in Equation (2), with identical demand functions $\mathcal{D}_i\left(\widetilde{p};\varsigma\right) \equiv \mathcal{D}\left(\widetilde{p};\varsigma\right)$, which are nonnegative-valued and decreasing for all $\widetilde{p} \leq \underline{\widetilde{p}}$ for a relative choke price $\underline{\widetilde{p}}$. This demand system can rationalized by a homothetic utility function (aggregator) Q_t as a

[21]Table C.1 in Appendix C.1 provides additional details and displays summary statistics for our sample.

[22]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.

[23]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.

function of a vector of quantities $\boldsymbol{q}_t \equiv (q_{it})_{i\in V_t}$, implicitly defined through

$$\sum_{i\in V_t} \mathcal{K}\left(\frac{q_{it}}{Q_t};\varsigma\right) = \mathcal{K}(1), \tag{25}$$

where the Kimball function is given by $\mathcal{K}(\widetilde{q}) \equiv \int_0^{\widetilde{q}} \mathcal{D}^{-1}(v;\varsigma)\,dv$ for the corresponding demand function $\mathcal{D}(\cdot;\varsigma)$.

We consider a number of different parameterizations of the Kimball function, characterized using the *Kimball elasticity* functions:

$$\mathcal{E}(\widetilde{q};\varsigma) \equiv -\frac{\widetilde{q}\,\mathcal{K}''(\widetilde{q};\varsigma)}{\mathcal{K}'(\widetilde{q};\varsigma)} = \frac{1}{\sigma\left(\mathcal{D}^{-1}(\widetilde{q};\varsigma)\right)}, \tag{26}$$

where in the second equality we have used the definition of the demand elasticity function in Equation (12), and the demand relations $\mathcal{K}'(\widetilde{q};\varsigma) = \mathcal{D}^{-1}(\widetilde{q};\varsigma)$ and $\widetilde{q} = \mathcal{D}(\widetilde{p};\varsigma)$. Given our assumptions on the Kimball function $\mathcal{K}(\cdot)$, the elasticity function $\mathcal{E}(\cdot)$ is positive-valued for all $\widetilde{p} < \underline{\widetilde{p}}$.[24]

We recover standard CES preferences by choosing Kimball function $\mathcal{K}(\widetilde{q};\varsigma) \equiv \widetilde{q}^{1-1/\sigma}$ in Equation (25) with the corresponding choice of parameterization $\varsigma \equiv (\sigma)$. Below, we consider three additional parametric families of Kimball functions $\mathcal{K}(\cdot;\varsigma)$, each characterized by a corresponding family of elasticity functions $\mathcal{E}(\cdot;\varsigma)$.

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

$$\mathcal{E}(\widetilde{q};\varsigma) \equiv \frac{\widetilde{q}^{\theta}}{\sigma}, \qquad \varsigma \equiv (\sigma,\theta) \tag{27}$$

   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

$$\mathcal{E}(\widetilde{q};\varsigma) \equiv \frac{1}{\sigma + (\sigma_o - \sigma)\,\widetilde{q}^{-\theta}}, \qquad \sigma < \sigma_o,\ \theta > 0,\ \varsigma \equiv (\sigma,\sigma_o,\theta), \tag{28}$$

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

[24] 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).

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

$$\mathcal{E}\left(\widetilde{q};\varsigma\right) \equiv \frac{1}{\sigma_o} + \left(\frac{1}{\sigma} - \frac{1}{\sigma_o}\right)\frac{e^{\theta_o}\widetilde{q}^{\theta}}{1+e^{\theta_o}\widetilde{q}^{\theta}}, \qquad \sigma < \sigma_o,\, \theta > 0,,\, \varsigma \equiv \left(\sigma, \sigma_o, \theta, \theta_o\right), \quad (29)$$

that goes from a finite value $1/\sigma_o$ to another finite value $1/\sigma$ as the normalized quantity goes from zero to infinity.[25]

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

3.3 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 a homothetic with aggregator (HA) demand system, e.g., 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 substitution σ:

$$\log s_{it} = -(\sigma - 1)\,\log p_{it} + \beta \boldsymbol{x}_{it} + make_i + \delta_t + \epsilon_{it}, \quad (30)$$

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

[25]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.

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 (30) using ordinary least squares, as an additional benchmark for the instrumented regressions.

We also estimate Equation (30) with the DP approach, using the moment conditions in first-differences as in Equation (10) 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).[26]

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 (29), (28) and (27), using the moment condition in Equation (9). 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.

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

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 specifcations 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).

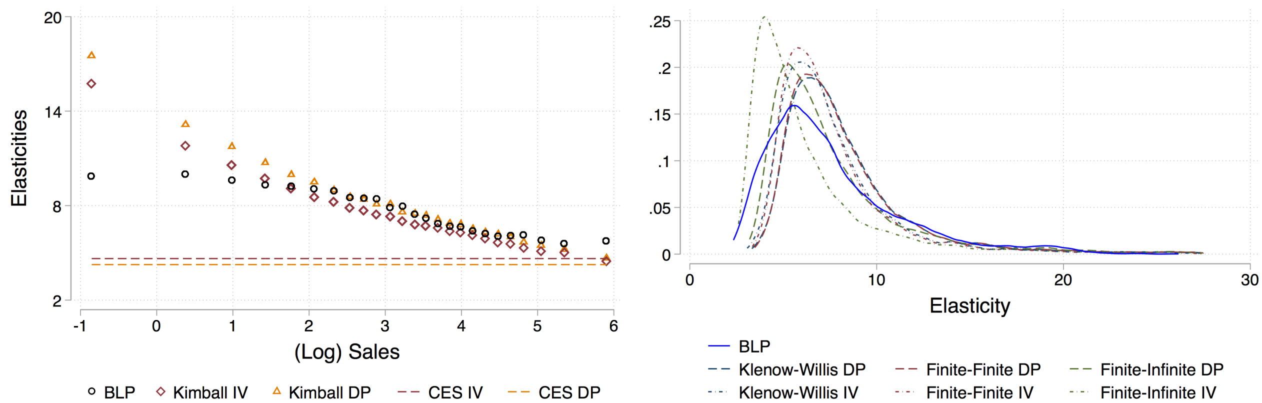
3.4 The Comparison of Estimated Own-Price Elasticities

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 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

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.

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 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.

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 and using the two different identification strategies.[27] This result, in addition to the evidence on the similarity of the interquartile 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.[28] 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).

3.5 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. 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 alternative 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 (5) 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 (5).[29] We then study the correlation between the quality measure φ_{it} (inferred using either the CES or Kimball estimates) and a subset of product characteristics tightly linked to product quality in this specific market, e.g., horsepower, space, miles-per-dollar and style:

$$\varphi_{it} = \beta \boldsymbol{x}_{it} + \eta_t + \gamma_i + \epsilon_{it}, \tag{31}$$

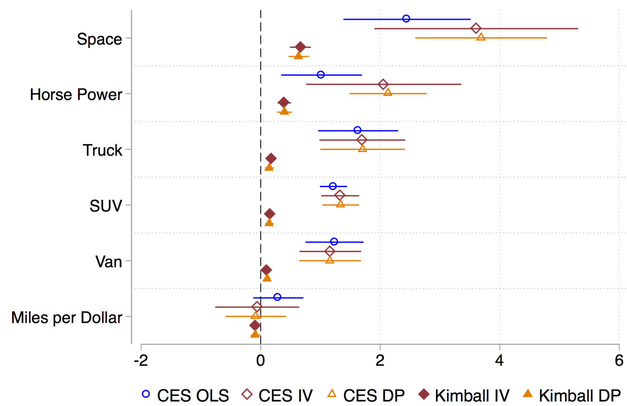
where $\boldsymbol{x}_{it}$ is the set of characteristics listed above. The correlation coefficients estimated from regression (31) are compared against the coefficients estimated from Equation (30)

[27] See also Figure C.1 in Appendix C for additional comparisons across Kimball specifications and identification strategies.

[28] 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.

[29] See the discussion in Appendix B.3 for more details on inverting the Kimball 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 (5). For the Kimball specification, inferred quality is obtained inverting demand as in Appendix *B*.3. The coefficients referring to the DP approach (CES and Kimball) and the Kimball IV case are obtained from regression in Equation (31). 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 (30), 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.

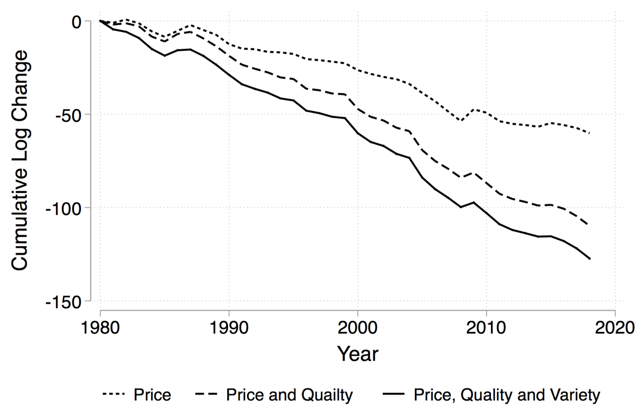
above.[30]

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 C.3 in Appendix C.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 C.3 shows

[30] We re-estimate Equation (30) above using the same set of product characteristics and fixed effects as in regression (31).

Figure 3: The Price Index for the US Auto Market



Note: The figure plots the 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.

that higher quality models have lower price elasticities and, thus, higher markups. The right panel of Figure C.3 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).[31]

3.6 Consumption Gains in the Auto Market

We construct the price index for the entire US auto market following Section 2.3 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.[32]

In Figure 3 we plot the Kimball price index for the US auto market over the 1980-2018 period, highlighting the role of the price, 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

[31]Consistent with this evidence, Figure C.4 in Appendix C.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). Moreover, these results are also consistent with Atkin et al. (2015), who show direct evidence for the relationship between markups and costs

[32]See footnote 26 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.[33] Table C.3 in Appendix C.3 compares the price index for Kimball to the 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). We find that our conclusions about the quantitative role of quality improvement for welfare changes strongly depend on our assumptions about the underlying structure of demand.[34]

4 Consumer Gains from Imports in the US

We now turn to the task of evaluating the impact of the changes in the size, content, and composition of US imports for the welfare of consumers in the United States from 1989 to 2006, as captured by the price index of US import. We first briefly outline a model of consumer demand for imports and define the corresponding price index building on the results of Section 2.3. 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 price index of US import.

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 $Q_{M,t} = \mathcal{F}_2(\boldsymbol{Q}_{M,t})$.

[33] 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.

[34] We can use our estimation results to explore the evolution of markups and marginal cost in the US auto market. Figure C.5 in Appendix C.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).

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

$$\sum_{i \in V_{kt}} \mathcal{K}\left(e^{\varphi_{kit}} \frac{q_{kit}}{Q_{kt}}; \varsigma_k\right) = \mathcal{K}(1), \tag{32}$$

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 (29)

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 composite 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 for any homothetic aggregator $\mathcal{F}_2(\cdot)$, up to the second order, using the Törnqvist price index (Diewert, 1976, 1978; Jaravel and Lashkari, 2021):

$$\Delta \log P_{M,t} \approx \sum_k \overline{\overline{s_{kt}}} \Delta \log P_{kt}, \tag{33}$$

where the Törnqvist sectoral weight $\overline{\overline{s_{kt}}}$ is the average share of sector k is the total volume of import between periods $t-1$ and t.

To compute the aggregate import price index from Equation (33), 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 2.3. As we discuss below, we first estimate the Kimball demand system, separately for each sector, using the technique presented in Section 2.2, and then use Equation (23) 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 the CES demand 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.[35] To minimize the effects of noise in the data, we trim the data as follows: 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 an 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).[36] We use our Dynamic Panel (DP) approach using the moment condition in Equation (10) 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.[37] We use the moment condition in Equation (9) with lagged log prices and quantities and their quadratic power as instruments.[38]

For the purpose of estimation, we use any continuously imported variety over the period from 1989 to 2006 within each product classification as the baseline product to infer quality in Equation (5).[39] For computing the price index, we create a basket of OECD countries as our set of baseline products O_k for quality ($\frac{1}{|O_k|}\sum_{o\in O_k}\varphi_{ot} = 0$) within each product classification, assuming that the average quality of varieties imported from these countries are on average the same as those reflected in the US CPI. This allows us to express the quality of the varieties supplied by all other countries relative to this baseline.

[35] In Appendix D.3 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.

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

[37] Note that the contribution of changes in the set of available varieties at more disaggregated levels, e.g., HS10, appears as quality gains at the SITC3 level. As we will discuss below, our measures of variety gains at SITC3 and HS10 levels are similar in the CES case, since the larger changes in the share of common varieties set in the more disaggregated case are mostly counteracted by the correspondingly lower love of variety (higher elasticities of substitution). We can extend our analysis to the more disaggregated levels, e.g., HS10, by focusing on shorter intervals of time over which we can define a continuously imported variety as a reference product in our estimation.

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

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

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.

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.[40] 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 the number for FBW and more than twice that for 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.[41]

As we discussed in Section 2.2.2, 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.

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 should be more substitutable (Broda and Weinstein, 2006). In Appendix D.1, we use the

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

[41] Figure D.6 in Appendix D.3 shows the strong correlation among the estimates found by the three methods.

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.

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.

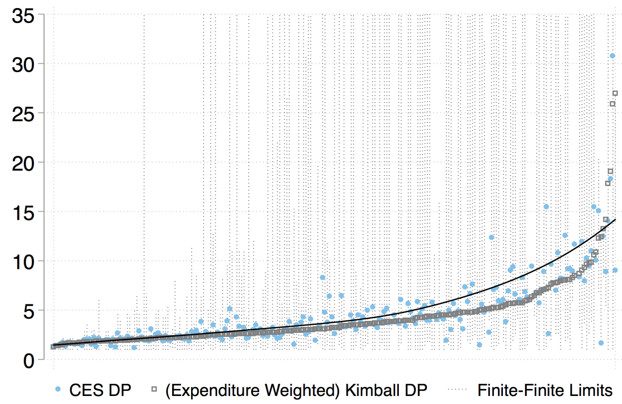
Elasticities under the Kimball Model We now turn our attention to the estimated price elasticities for the Kimball model and compare them to the corresponding CES estimates.[42] Table 3 compares different moments of the distribution of elasticities across varieties between Kimball and CES estimates.[43] 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.[44] However, the estimated lower and upper limits of the Finite-Finite specification

[42]Table D.4 in Appendix D.3 reports summary statistics of the distribution of the estimated Finite-Finite Kimball parameters.

[43]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.

[44]The CES elasticities reported in Figure 4 are estimated using CES as the limiting case of the Kimball specification ($\sigma_o \equiv \sigma$). Figure D.7 in Appendix D.3 shows that there is almost a perfect match between the

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.

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.[45]

In line with the results from the US auto market, Figure 5 shows that across all product codes, varieties with higher inferred quality have higher expenditure shares and lower price elasticities.

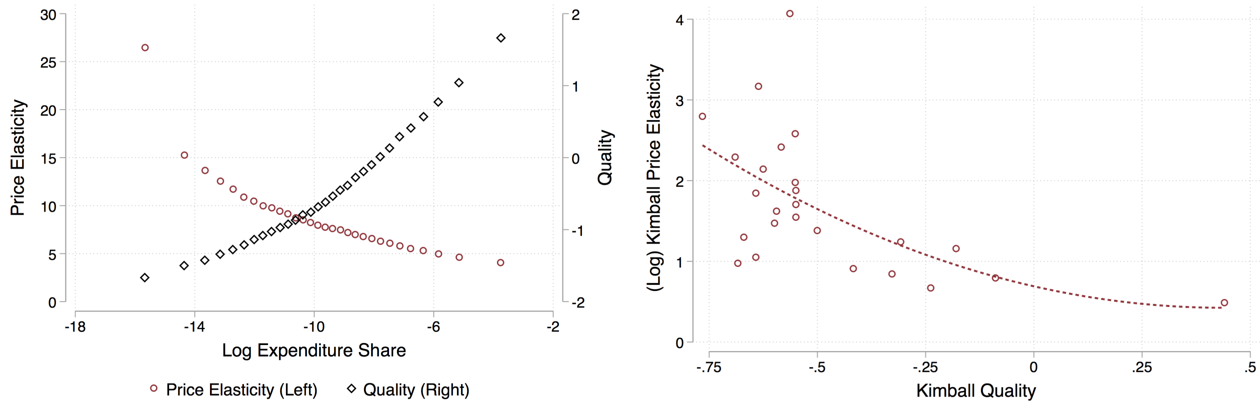
4.4 The Evolution of the US Import Price Index

Figure 6 reports the cumulative change in the aggregate price of US imports relative to the CPI from Equation (33), where the changes in the sector-level Kimball price indices are approximated using the expression in Equation (23). 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. A price index including only changes in unadjusted prices would find

estimates obtained using the limiting Kimball moment and the moment conditions in first-differences used for elasticities reported in Table D.1.

[45]Figure D.8 in Appendix D.3 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.

Figure 5: 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.

the cumulative decline in the aggregate import price index over the period to be around 11%.[46] Figure 6 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.[47]

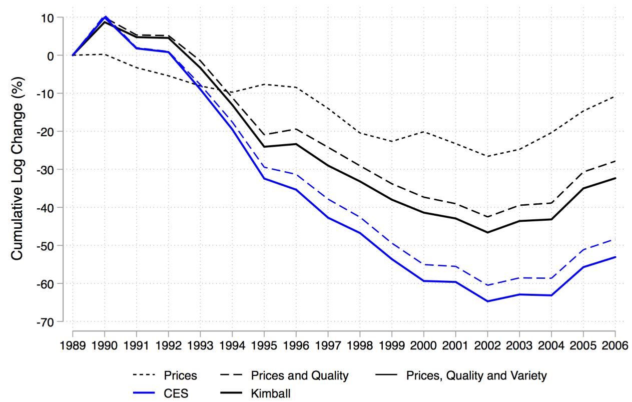
Using CES preferences instead of Kimball doubles the consumption gains arising from the product quality channel, leading to a sizable overestimation of the overall gains. The CES aggregate price index for imports shows a decline of around 53% (2.95% annually), 30% more than the Kimball case. The stark difference with respect to the Kimball aggregate price index arises mainly from the different 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 constant elasticity assumption in the standard CES demand systems for evaluating the consumption gains from trade, and in particular the role of product quality.

To better understand the drivers of the gap in the contribution of quality implied by CES and Kimball, Proposition A.1 in Appendix A.3 provides a decomposition of this

[46]Figure D.9 in Appendix D.3 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.

[47]In Appendix D.3, Figure D.10 and Table D.5 show the change in the price index of imports and its decomposition when the prices are stated relative to the US PPI. In this case, the unadjusted import prices in fact slightly rise over time and almost all of the fall in the import price index is explained by quality improvements.

Figure 6: 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 (19) and (23). 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.

gap to a number of different components. Appendix D.2.1 uses this decomposition to show that the key reason for the overestimation of the contribution of quality under the CES specification is simply that the corresponding estimated elasticities suffer from a downward bias.

The above results show that, although quantitatively less relevant than the role of quality upgrading, the contribution of variety in Lemma 2 also depends on the demand system used to evaluate it. The gains from varieties in the presence of heterogenous demand elasticities are smaller mainly because the index of love of variety, when adjusted for contribution of heterogeneity in demand elasticities, $\overline{\overline{\mu}}^{*}_{k,t}$, is typically smaller than in the CES case, $\mu_k \equiv \frac{1}{\sigma_k - 1}$. Once again, this result is driven by the lower estimates of the price elasticities under the CES case, which leads to an overestimation of the contribution of variety.

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 exporters 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

Table 4: Change in the Import Price Index in the US (Relative to CPI, 1989–2006)

	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 (19) and (23) and reported in Figure 6, 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.

average quality across OECD varieties.[48] The contribution of the OECD countries and all the other exporters to the overall quality improvement is about 20% and 14%, respectively.[49] 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 the quality upgrading already in progress in the 90s but accelerates after China's accession to the WTO. This result is 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), and with recent evidence for the substantial effect of the China's entry into the WTO on US prices (Amiti et al., 2020).[50]

5 Conclusion

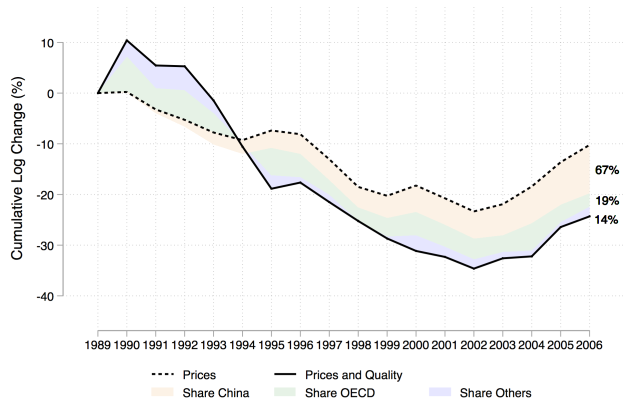
In this paper, we examined the role of quality improvements for the consumption gains from globalization in the context of the changes in the size and composition of US imports

[48]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.

[49]Figure D.11 in Appendix D.3 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.

[50]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 (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 E.1 for further discussion.

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).

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.

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Appendix to "The Quality of US Imports and the Consumption Gains from Globalization"

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Contents

A Additional Theoretical Results

A.1 Examples of Homothetic Demand Systems

Here, we show how a few popular choices of demand system can be written as the specification in Definition 1.

1. Mixed Logit (McFadden, 1974; Berry, 1994). This demand system is given through the choice of

$$\mathcal{S}_i\left(\widetilde{\boldsymbol{p}};\varsigma\right) \equiv \int_{\sigma\in\Sigma} \frac{\exp\left(-\sigma\log\widetilde{p}_i\right)}{\sum_{i'\in V_t}\exp\left(-\sigma\log\widetilde{p}_{i'}\right)} dF\left(\sigma;\varsigma\right), \qquad i\in V,$$

   with $\mathcal{H}\left(\boldsymbol{p};\varsigma\right) = \prod_{i\in V} p_i^{1/|V|}$.

2. Homothetic Translog (e.g., Diewert, 1976; Feenstra, 2003). This demand system is given through the choice of

$$\mathcal{S}_i\left(\widetilde{\boldsymbol{p}};\varsigma\right) \equiv \theta_i + \sum_{i'\in V} \sigma_{ii'}\log\widetilde{p}_{i'}, \qquad i\in V,$$

   with $\sum_{i\in V}\theta_i = 1$ and $\sigma_{ii'} = \sigma_{i'i}$ and $\sum_{i'}\sigma_{ii'} = 0$, and $\mathcal{H}\left(\boldsymbol{p};\varsigma\right) = \prod_{i\in V} p_i^{1/|V|}$. Note that this demand system also coincides with the AIDS demand system of Deaton and Muellbauer (1980) when the latter is restricted to be homothetic.

3. Homothetic with a Single Aggregator (HSA) (Matsuyama and Ushchev, 2017; Matsuyama, 2022). This demand system is given by

$$\mathcal{H}\left(\boldsymbol{p};\varsigma\right) = h, \text{ such that } \sum_{i\in V_t}\mathcal{S}_i\left(\frac{\boldsymbol{p}}{h};\varsigma\right) = 1.$$

   We may particularly focus on the family $\mathcal{S}_i\left(\cdot;\varsigma\right)$ defined as[A1]

$$\log\mathcal{S}_i\left(\boldsymbol{p};\varsigma\right) \equiv \log\mathcal{S}\left(p_i;\varsigma\right) \equiv -\int_o^{\log p_i}\exp\left(\sum_{k=0}^{K}\theta_k x^k\right)dx, \tag{A.1}$$

   where $\varsigma \equiv \left(\theta_0,\cdots,\theta_K\right)$ are the parameters of the family. Note that Equation (A.1) nests CES demand for the case of $\theta_0 = \log\left(\sigma-1\right)$ and $\theta_k = 0$ for $k\geq 1$. In particular, the elasticity of demand for the product i at time t corresponding to the HSA

[A1] The expression in Equation (A.1) 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. Since $d\log\mathcal{S}(p)/d\log p < 0$, the implication is that all products are gross substitutes everywhere.

demand in Equation (A.1) is given by

$$\left.\frac{\partial \log q_i}{\partial \log p_i}\right|_{h\,\text{const.}} = -\left[1+\exp\left(\sum_{k=0}^{K}\theta_k\left(\log p_i\right)^k\right)\right],$$

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

A.2 Second-Order Approximation of the Change in Price Index for HSA/HIA

We can provide second order approximations for the change in the unit expenditure function for the HSA/HIA demand systems introduced in Definition 3. Using Proposition 1 and Lemma 1, we find the following approximations in the case of each demand system

$$\begin{aligned}
\Delta \log P_t &\approx \sum_{i\in V_t^*}\overline{\overline{s_{it}^*}}\,\Delta \log p_{it} - \sum_{i\in V_t}\overline{\overline{s_{it}^*}}\,\Delta\varphi_{it} \\
&\quad + \overline{\overline{\overline{\mu}_t^*}}\,\Delta\log\Lambda_t^* + \sum_{i\in V_t^*}\overline{\overline{\mu_{it}}}\,\Delta s_{it}^* - \begin{cases}\sum_{i\in V}\overline{\overline{\mu}}_{it}\,\Delta s_{it}, & \text{HSA},\\ \sum_{i\in V}\overline{\overline{\left(\left(1+\frac{\overline{\mu}_t^*-\overline{\mu}_t}{1+\overline{\mu}_t}\right)\mu_{it}\right)}}\,\Delta s_{it}, & \text{HIA}.\end{cases} && \text{(A.2)}\\
&\approx \langle\Delta\log p_{it}\rangle + \langle\overline{\overline{\mu}}_{it}\,\Delta\log s_{it}^*\rangle && \text{(A.3)}\\
&\quad + \overline{\overline{\langle\mu_{it}\rangle}}\,\Delta\log\Lambda_t^* - \begin{cases}\sum_{i\in V}\overline{\overline{\mu}}_{it}\,\Delta s_{it}, & \text{HSA},\\ \sum_{i\in V}\overline{\overline{\left(\left(1+\frac{\langle\mu_{it}\rangle-\overline{\mu}_t}{1+\overline{\mu}_t}\right)\mu_{it}\right)}}\,\Delta s_{it}, & \text{HIA}.\end{cases} && \text{(A.4)}
\end{aligned}$$

The proof of the result closely follows that of Lemma 2 to approximate the integrals in Equations (14) and (16), with the additional simplification given by Equation (22), over time τ from $t-1$ to t.

A.3 The Gap Between the CES- and Kimball-Inferred Quality Contribution

We study the implications of inferring quality if we misspecify the underlying Kimball preferences to be CES. The next proposition compares the contribution of quality changes under CES and Kimball.

Proposition A.1. *Consider using a misspecified CES demand system with elasticity of substitution σ^c to infer quality φ_{it}^c based on observed sequences of prices and quantities that are rationalized by an underlying Kimball demand system. The gap between the true and the misspecified measures* *of quality change is approximately given by*

$$\sum_{i \in V_t^*} \overline{\overline{s_{it}^*}} \left(\Delta \varphi_{it} - \Delta \varphi_{it}^c\right) \approx \left\langle \left(\mu^c - \overline{\overline{\mu_{it}}}\right) \Delta \log s_{it}^* \right\rangle + \sum_{i \in V_t^*} \overline{\overline{s_{i\tau}^* \mu_{i\tau}}} \Delta \log s_{i\tau}^*$$
$$+ \left(\overline{\overline{\mu_\tau^*}} - \overline{\overline{\langle \mu_{it} \rangle}}\right) \left(\Delta \log \Lambda_t^* + \Delta \log A_t\right), \qquad \text{(A.5)}$$

where, as before, $\overline{\overline{v_{it}}} \equiv \frac{1}{2}(v_{it-1} + v_{it})$ *stands for the Törnqvist mean of variable* v_{it}*, and where* $\mu^c \equiv \frac{1}{\sigma^c - 1}$.

Proof. See Appendix B.1. □

The first term on the right hand side of Equation (A.5) (CES-Baseline Gap) 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 μ^c exceeds the average of the Kimball proxies $\overline{\overline{\mu_{it}}}$, 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 on the right hand side of Equation (A.5) (Elasticity Heterogeneity) 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 (A.5) (CVS-Baseline Gap), 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 $\sigma_{it} \equiv \sigma$.

A.4 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 a CES demand specification presented in Section 2.2.1, which 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 $\widehat{p}_{it} \equiv p_{it}/p_{ot}$ in a simple setting where the set of base products is a singleton $O \equiv \{o\}$, and where, as before, φ_{it} stands for the demand shock. The Leamer–Feenstra approach to identification begins with positing a supply relationship of the form

$$\Delta \log \widehat{p}_{it} = \zeta \log \Delta \widehat{q}_{it} + \Delta \xi_{it}, \tag{A.6}$$

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 $z_{it}^{F-L}(\zeta) \equiv \Delta \log \widehat{p}_{it} - \zeta \log \Delta \widehat{q}_{it}$ that allows us to identify σ through the moment condition

$$\mathbb{E}\left[\left(\Delta \log \widehat{q}_{it} + \sigma \Delta \log \widehat{p}_{it}\right) \times z_{it}^{F-L}(\zeta)\right] = 0. \tag{A.7}$$

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 ($\mathbb{V}\left[\Delta \varphi_{it}\right] / \mathbb{V}\left[\Delta \xi_{it}\right] \neq \mathbb{V}\left[\Delta \varphi_{jt}\right] / \mathbb{V}\left[\Delta \xi_{jt}\right]$).[A2] 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 (A.7) 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 (A.6) with our pricing Equation (11). 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, 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.

[A2] See also Soderbery (2015) for a detailed discussion of how this condition helps identify the elasticities using specific examples from trade data.

In contrast, our approach begins by assuming a simple dynamic process like that of Equation (7) on demand shocks. The same pricing Equation (11) 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 (7) 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 Proofs and Derivations

B.1 Proofs

Proof for Proposition 1. First, for the HA demand, defined by Equations (3) and (1), the change in log expenditure share of product $i \in V$ satisfies

$$d \log s_{i\tau} = -\left(\sigma_{i\tau} - 1\right)\left(d \log p_{i\tau} - d \log \varphi_{i\tau} - d \log H_\tau\right) - d \log A_\tau, \tag{B.1}$$

where $\sigma_{i\tau}$ is defined by Equation (12), and where $H_\tau \equiv \mathcal{H}\left(\left(e^{-\varphi_{i\tau}} p_{i\tau}\right)_{i \in V}; \varsigma\right)$ and $A_\tau \equiv \sum_{i \in V}\left(e^{-\varphi_{i\tau}} \frac{p_{i\tau}}{H_\tau}\right) \mathcal{D}_i\left(e^{-\varphi_{i\tau}} \frac{p_{i\tau}}{H_\tau}\right)$. Equation (B.1), in turn, leads to the following equality for any $i \in V$:

$$d \log p_{i\tau} - d\varphi_{i\tau} = d \log H_\tau - \mu_{i\tau}\left(d \log A_\tau + d \log s_{i\tau}\right). \tag{B.2}$$

Now, we can expand the change in the unit expenditure function of any homothetic preferences as

$$d\log P_\tau = \sum_{i\in V} \frac{\partial \log P_\tau}{\partial \log p_{i\tau}} \left(d\log p_{i\tau} - d\varphi_{i\tau}\right) = \sum_{i\in V_{t-1}\cup V_t} s_{i\tau}\left(d\log p_{i\tau} - d\log \varphi_{i\tau}\right), \tag{B.3}$$

where we have used the Shephard's lemma in the second equality. Substituting from Equation (B.2) in Equation (B.3), we find

$$d\log P_t = d\log H_\tau - \overline{\mu}_\tau d\log A_\tau - \sum_{i\in V_{t-1}\cup V_t} \mu_{i\tau} ds_{i\tau}, \tag{B.4}$$

where $\overline{\mu}_\tau \equiv \sum_{i\in V_{t-1}\cup V_t} s_{i\tau}\mu_{i\tau}$.

Now, we compute the change in the logarithm of the expenditure share of common set

$$\begin{aligned} d\log \Lambda_t^* &= \frac{\sum_{i\in V_t^*} ds_{i\tau}}{\Lambda_\tau^*} = \sum_{i\in V_t^*} s_{it}^* d\log s_{i\tau}, \\ &= -\sum_{i\in V_t^*} s_{it}^*\left(\sigma_{i\tau}-1\right)\left(d\log p_{i\tau} - d\log\varphi_{i\tau} - d\log H_\tau\right) - d\log A_\tau, \\ &= -\left(\overline{\sigma}_\tau^*-1\right)\left(d\log\left(\frac{D_\tau^*}{\Phi_\tau^*}\right) - d\log H_\tau\right) - d\log A_\tau - \mathbb{C}^*\left(\sigma_{i\tau}, d\log p_{i\tau} - d\varphi_{i\tau}\right), \end{aligned} \tag{B.5}$$

where in the second line, we have used Equation (B.1), and where in the third line we have used the definitions of the Divisia and Quality indices in Equation (15), and have defined the covariance between the demand elasticity σ_{it} and the change in quality-adjusted prices as

$$\mathbb{C}^*\left(\sigma_{it}, d\log p_{it} - d\varphi_{it}\right) \equiv \sum_{i\in V_t^*} s_{it}^*\left(\sigma_{i\tau} - \overline{\sigma}_\tau^*\right)\left(d\log p_{i\tau} - d\log\varphi_{i\tau}\right).$$

We now use Equation (B.5) to substitute for $d\log H_\tau$ in Equation (B.4) and find:

$$\begin{aligned} d\log P_\tau = {} & d\log\left(\frac{D_\tau^*}{\Phi_\tau^*}\right) + \frac{1}{\overline{\sigma}_\tau^*-1} d\log\Lambda_t^* + \left(\frac{1}{\overline{\sigma}_\tau^*-1} - \overline{\mu}_\tau\right) d\log A_\tau \\ & + \frac{1}{\overline{\sigma}_\tau^*-1}\mathbb{C}^*\left(\sigma_{i\tau}, d\log p_{i\tau} - d\varphi_{i\tau}\right) - \sum_{i\in V_{t-1}\cup V_t} \mu_{i\tau} ds_{i\tau}. \end{aligned} \tag{B.6}$$

The last step for proving Equation (14) is to compute the covariance term. Using Equation (B.2), we can rewrite this covariance as $\mathbb{C}^*\left(\sigma_{i\tau}, d\log p_{i\tau} - d\varphi_{i\tau}\right) = -\mathbb{C}^*\left(\sigma_{i\tau}, \mu_{i\tau}\right) d\log A_\tau -$

$\mathbb{C}^*\left(\sigma_{i\tau}, \mu_{i\tau} d\log s_{i\tau}\right)$. The first term can be simplified to:

$$\mathbb{C}^*\left(\sigma_{i\tau}, \mu_{i\tau}\right) = \sum_{i\in V_t^*} s_{i\tau}^*\left(\sigma_{i\tau} - \overline{\sigma}_\tau^*\right)\mu_{i\tau} = 1 - \overline{\mu}_\tau^*\left(\overline{\sigma}_\tau^* - 1\right),$$

while the second term can be written as

$$\begin{aligned}
\mathbb{C}^*\left(\sigma_{i\tau}, \mu_{i\tau} d\log s_{i\tau}\right) &= \sum_{i\in V_t^*} s_{i\tau}^*\left(\sigma_{i\tau} - \overline{\sigma}_\tau^*\right)\mu_{i\tau} d\log s_{i\tau}, \\
&= \sum_{i\in V_t^*} s_{i\tau}^*\left(\sigma_{i\tau} - \overline{\sigma}_\tau^*\right)\mu_{i\tau}\left(d\log\Lambda_\tau^* + d\log s_{i\tau}^*\right), \\
&= \left[1 - \overline{\mu}_\tau^*\left(\overline{\sigma}_\tau^* - 1\right)\right] d\log\Lambda_\tau^* \\
&\quad + \sum_{i\in V_t^*} s_{i\tau}^*\left(1 - \mu_{i\tau}\left(\overline{\sigma}_\tau^* - 1\right)\right) d\log s_{i\tau}^*, \\
&= \left[1 - \overline{\mu}_\tau^*\left(\overline{\sigma}_\tau^* - 1\right)\right] d\log\Lambda_\tau^* - \left(\overline{\sigma}_\tau^* - 1\right)\sum_{i\in V_t^*}\mu_{i\tau} ds_{i\tau}^*.
\end{aligned}$$

Combining the two terms, we find

$$\mathbb{C}^*\left(\sigma_{i\tau}, d\log p_{i\tau} - d\varphi_{i\tau}\right) = \left(\overline{\sigma}_\tau^* - 1\right)\left[\sum_{i\in V_t^*}\mu_{i\tau} ds_{i\tau}^* - \left(\frac{1}{\overline{\sigma}_\tau^* - 1} - \overline{\mu}_\tau^*\right)\left(d\log\Lambda_\tau^* + d\log A_\tau\right)\right].$$

Substituting the above expression in Equation (B.6) leads to Equation (14).

To prove Equation (16), we use Equation (B.2) , and the normalization that $\langle d\varphi_{i\tau}\rangle \equiv 0$, to find

$$d\log H_\tau = \langle d\log p_{i\tau}\rangle + \langle \mu_{i\tau} d\log s_{i\tau}\rangle + \langle \mu_{i\tau}\rangle\, d\log A_t. \tag{B.7}$$

Using the definitions in Equation (15) and Equation (B.2), and using the above result leads to

$$d\log\left(\frac{D_\tau^*}{\Phi_\tau^*}\right) = \langle d\log p_{i\tau}\rangle + \langle \mu_{i\tau} d\log s_{i\tau}\rangle + \left(\langle \mu_{i\tau}\rangle - \overline{\mu}_\tau^*\right) d\log A_t - \sum_{i\in V_t^*} s_{i\tau}^*\mu_{i\tau} d\log s_{i\tau},$$

which in turn leads to the desired result if we note that $d\log s_{i\tau} = d\log s_{i\tau}^* + d\log\Lambda_\tau^*$. □

Proof for Lemma 1. The case of HSA trivially follows from the observation that $d\log A_\tau \equiv 0$. In the HIA case, the results of Matsuyama and Ushchev (2017) along with the definitions of the indices H_τ and A_τ imply that $P_\tau = A_\tau H_\tau$. Combining $d\log P_\tau = d\log H_\tau +$

$d\log A_\tau$ and Equation (B.4) implies

$$d\log A_\tau = -\frac{1}{1+\overline{\mu}_\tau}\sum_{i\in V} s_{i\tau}\mu_{i\tau} d\log s_{i\tau},$$

which, using the leads to the desired result. □

Proof for Lemma 2. We use the following standard result on the error of the trapzoidal integration rule:

$$I \equiv \int_{v_{\tau-1}}^{v_\tau} f(v)\ dv = \sum_j \tfrac{1}{2}\left(f\left(v_{t-1}\right)+f\left(v_{t-1}\right)\right)\left(v_t - v_{t-1}\right) - \frac{1}{12}f''\left(v^\dagger\right)\left(v_t - v_{t-1}\right)^3, \tag{B.8}$$

for some $v^\dagger \in [v_{t-1}, v_t]$. From this, it then follows that $I = \overline{\overline{f(v_t)}}\Delta v_t + O\left(|\Delta v_t|^3\right)$. We apply this result to each of the terms in Equation (14). For instance, doing a change of variable $v \equiv \log p_{i\tau}$, we find for the first term (from Equation 15) that

$$\int_{t-1}^{t} s^*_{i\tau} d\log p_{i\tau} = \int_{\log p_{it-1}}^{\log p_{it}} s^*_i(v)\,dv = \overline{\overline{s^*_{it}}}\,\Delta\log p_{it} + O\left(|\Delta\log p_{it}|^3\right).$$

Applying the same treatment to the other terms leads to the desired result. □

Proof of Proposition A.1. Let σ^c denote the constant CES elasticity and consider the same path as that in Proposition 1 between periods $t-1$ and t. From Equations (B.2) and (B.7), the inferred change in quality under the Kimball and the CES demand are given by

$$\begin{aligned} d\varphi_{i\tau} &= d\log p_{i\tau} + \mu_{i\tau} d\log s_{i\tau} - \langle d\log p_{i\tau}\rangle - \langle \mu_{i\tau} d\log s_{i\tau}\rangle + \left(\mu_{i\tau} - \langle\mu_{i\tau}\rangle\right) d\log A_\tau, \\ d\varphi^c_{i\tau} &= d\log p_{i\tau} + \mu^c d\log s_{i\tau} - \langle d\log p_{i\tau}\rangle - \mu^c\langle d\log s_{i\tau}\rangle, \end{aligned}$$

where we have let $\mu^c \equiv \frac{1}{\sigma^c - 1}$. We can therefore write

$$\begin{aligned} \sum_{i\in V^*_t} s^*_{i\tau}\left(d\varphi_{i\tau} - d\varphi^c_{i\tau}\right) &= \sum_{i\in V^*_t} s^*_{i\tau}\left(\mu_{i\tau} - \mu^c\right) d\log s_{i\tau} + \tfrac{1}{|O|}\sum_{i\in O}\left(\mu^c - \mu_{i\tau}\right) d\log s_{i\tau} \\ &\quad + \left(\overline{\mu}^*_\tau - \langle\mu_{i\tau}\rangle\right) d\log A_\tau, \\ &= \sum_{i\in V^*_t} s^*_{i\tau}\mu_{i\tau} d\log s^*_{i\tau} + \tfrac{1}{|O|}\sum_{i\in O}\left(\mu^c - \mu_{i\tau}\right) d\log s^*_{i\tau} \\ &\quad + \left(\overline{\mu}^*_\tau - \langle\mu_{i\tau}\rangle\right)\left(d\log A_\tau + d\log\Lambda^*_\tau\right). \end{aligned}$$

Approximating this integral following the same arguments as in the proof of Corollary 2 leads to

$$\sum_{i\in V_t^*} s_{i\tau}^* \left(\Delta\varphi_{i\tau} - \Delta\varphi_{i\tau}^c\right) \approx \sum_{i\in V_t^*} \overline{\overline{s_{i\tau}^*\mu_{i\tau}}} \Delta \log s_{i\tau}^* + \left\langle \left(\mu^c - \overline{\overline{\mu_{i\tau}}}\right) \Delta \log s_{i\tau}^* \right\rangle$$
$$+ \left(\overline{\overline{\mu}}_t^* - \overline{\overline{\langle \mu_{it} \rangle}}\right) \left(\Delta \log \Lambda_t^* + \Delta \log A_t\right).$$

□

B.2 Derivations for Kimball Specifications

Below, we derive the Kimball functions corresponding to each of the three cases discussed in Section 3.2. 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:

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

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

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

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

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

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

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

$$\mathcal{K}\left(\widetilde{q}\right) = e^{\xi} \int_{0}^{\log \widetilde{q}} \left(\frac{\sigma v^{\theta} + \sigma_o - \sigma}{\sigma_o - \sigma}\right)^{-\frac{1}{\sigma\theta}} dv,$$

$$= e^{\xi}\, \widetilde{q} \cdot {}_2F_1\left(\frac{1}{\theta}, \frac{1}{\sigma\theta}; 1 + \frac{1}{\theta}; -\frac{\sigma}{\sigma_o - \sigma}\widetilde{q}^{\theta}\right),$$

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

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

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:

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

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

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

where ${}_2F_1$ is the hypergeometric function.

B.3 Inverting Kimball Demand

We implement the demand inversion through the dual problem, meaning that we map the vector of observed expenditure shares $\boldsymbol{s}_t$ to a corresponding vector of normalized quantities $\widetilde{\boldsymbol{q}}_t$. Formally, we solve for the function $\mathcal{D}\left(\pi_i\left(\cdot;\varsigma\right);\varsigma\right)$ corresponding to the definition (25).

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

$$\log s_{it} = \log \widetilde{q}_{it} + \psi\left(\log \widetilde{q}_{it}\right) - \log\left[\sum_{j \in V_t}\exp\left(\log \widetilde{q}_{jt} + \psi\left(\log \widetilde{q}_{jt}\right)\right)\right], \qquad \forall i \in V_t, \quad \text{(B.9)}$$

$$k(1) = \log \left[\sum_{i \in V_t} \exp\left(k\left(\log \widetilde{q}_{it}\right)\right) \right], \tag{B.10}$$

where $k(\cdot) \equiv \log \mathcal{K}(\exp(\cdot))$ and $\psi(\cdot) \equiv \log \mathcal{K}'(\exp(\cdot))$. We can rewrite Equation (B.9) as (assuming $O \equiv \{o\}$):

$$\log\left(\frac{s_{it}}{s_{ot}}\right) = \log\left(\frac{\widetilde{q}_{it}}{\widetilde{q}_{ot}}\right) + \psi\left(\log \widetilde{q}_{it}\right) - \psi\left(\log \widetilde{q}_{ot}\right), \qquad \forall i \in V_t. \tag{B.11}$$

Using the identity

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

we can substitute Equation (B.11) in Equation (B.10), we find:

$$\begin{aligned}
k(1) &= \log \left[\sum_{i \in V_t} \exp\left(k\left(\log \widetilde{q}_{it}\right)\right) \right], \\
&= \log \left[\sum_{i \in V_t} \exp\left(\log \widetilde{q}_{it} + \psi\left(\log \widetilde{q}_{it}\right) - k'\left(\log \widetilde{q}_{it}\right)\right) \right], \\
&= \log \left[\sum_{i \in V_t} \exp\left(\log \widetilde{q}_{ot} + \psi\left(\log \widetilde{q}_{ot}\right) + \log\left(\frac{s_{it}}{s_{ot}}\right) - k'\left(\log \widetilde{q}_{it}\right)\right) \right], \\
&= \log \widetilde{q}_{ot} + \psi\left(\log \widetilde{q}_{ot}\right) + \log \left[\sum_{i \in V_t} \frac{s_{it}}{s_{ot}} \exp\left(-k'\left(\log \widetilde{q}_{it}\right)\right) \right], \\
&= k\left(\log \widetilde{q}_{ot}\right) + \log \left[\sum_{i \in V_t} \frac{s_{it}}{s_{ot}} \exp\left(k'\left(\log q_{ot}\right) - k'\left(\log \widetilde{q}_{it}\right)\right) \right].
\end{aligned} \tag{B.12}$$

We use an iterative approach: starting with some initial guess for $\widetilde{q}_{ot}$, we iterate between updating values of $\widetilde{q}_{it}$ for $i \neq o$ from Equation (B.11) and updating the value of $\widetilde{q}_{ot}$ from Equation (B.12).

C Details on the Auto Data

C.1 Data

Table C.1: 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).

C.2 Testing the Identification Assumption

We are able to test the identification assumption in Equation (8) 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 (6), 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 (7), 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:

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

where $\boldsymbol{x}_{it-1}$ is the entire set of lagged product characteristics. Table C.2 reports the set of coefficients estimated using Equation (C.1). No estimated $\widehat{\alpha}$ coefficients are 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.[A3] We also standardize all variables and re-estimate Equation (C.1) 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.

[A3] The only exception is Truck, which exhibits a weak autocorrelation.

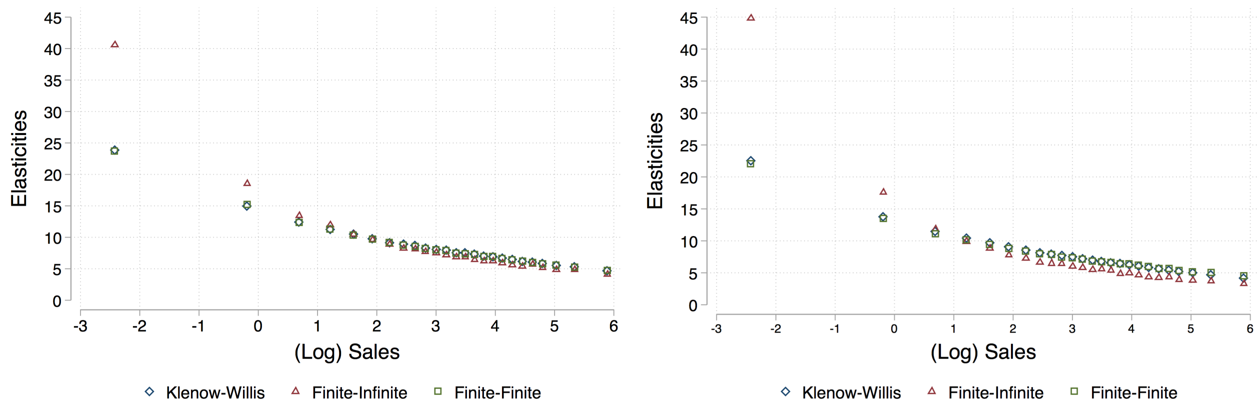
Table C.2: Testing the Identification Assumption

	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 (C.1). Each column refers to a given product characteristics. We consider horsepower, space, miles-per-dollar, truck, van and suv. For each characteristic, Equation (C.1) is estimated using level or z-score variables. Z-score variable refers to the set of coefficients estimated using Equation (C.1) after standardizing all variables. Standard errors are clustered at the model level.

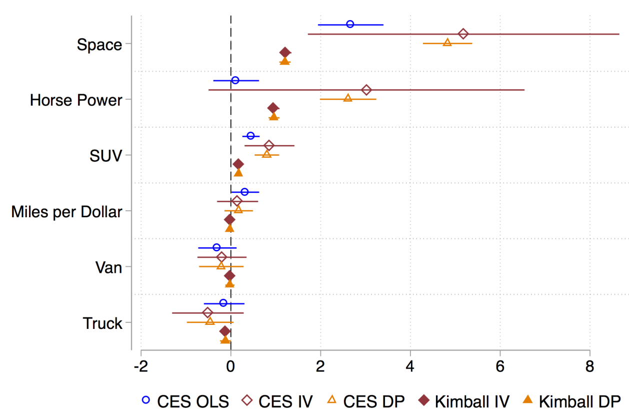
C.3 Additional Tables and Figures

Figure C.1: Comparison across Kimball Specifications



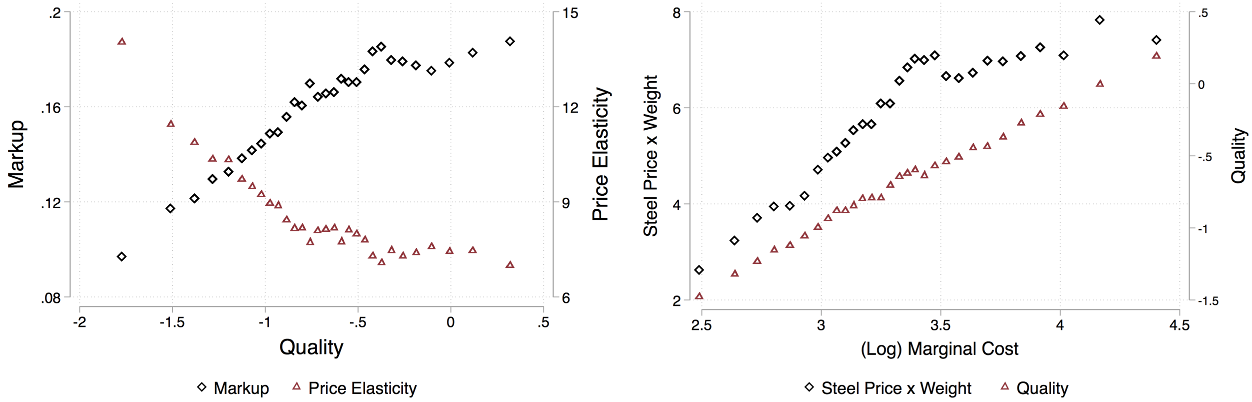
Note: The left panel shows a binscatter representation of the relationship between (log) sales and the Kimball price elasticities estimated using the DP approach. The right panel shows the relationship between (log) sales and Kimball price elasticities estimated using the IV approach. All three Kimball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

Figure C.2: Correlation between Inferred Quality and Product Characteristics



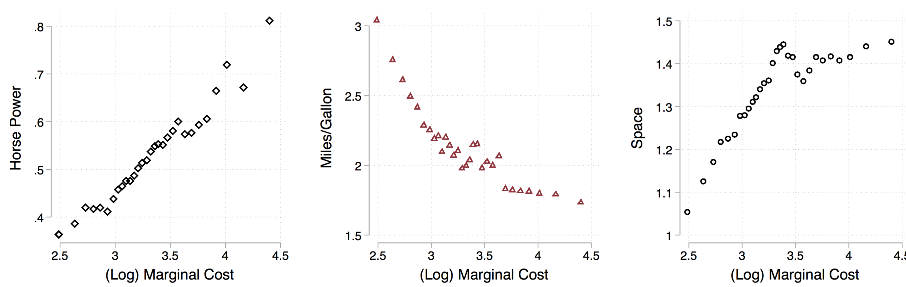
Note: The figure reports the relationship between product characteristics and quality inferred using Equation (5) for CES and Kimball demand systems. The coefficients referring to the DP approach (CES and Kimball) and the Kimball IV case are obtained from regression in Equation (31). We consider the 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 (30), 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 C.3: Markups and Marginal Cost



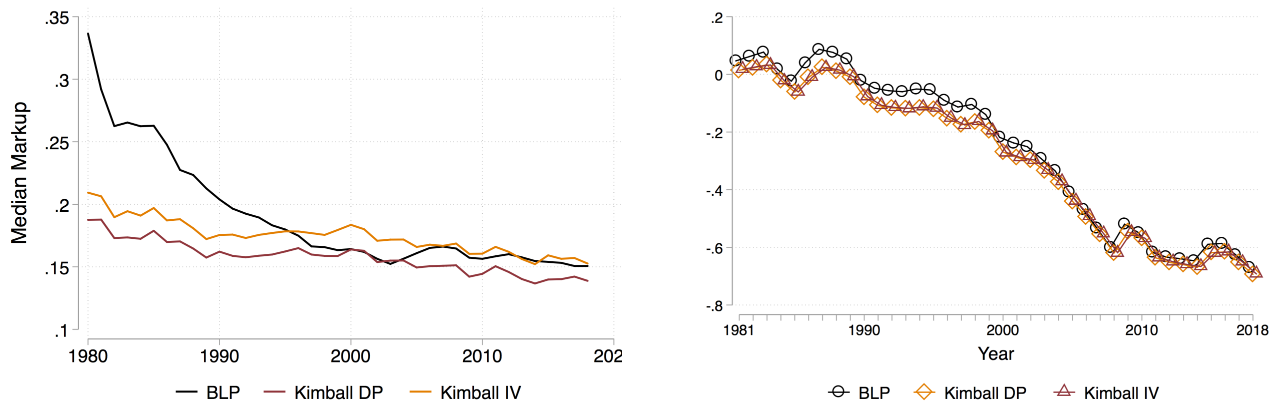
Note: The left panel shows the relationship between the measure of inferred quality and the price elasticity estimated from the Finite-Finite Kimball specification using the DP approach. Markups are computed under the assumption of monopolistic competition, $\mu_{it} = \frac{1}{\sigma_{it}-1}$, where 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 C.4: 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 C.5: 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 C.3: 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.

D Details on the US Import Data

D.1 Further Examination of CES Estimates

Price Elasticities Across Different Levels of Aggregation Table D.1 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 elasticities 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.[A4]

Table D.1: CES Elasticities based on the DP Approach at Different Levels of Aggregation

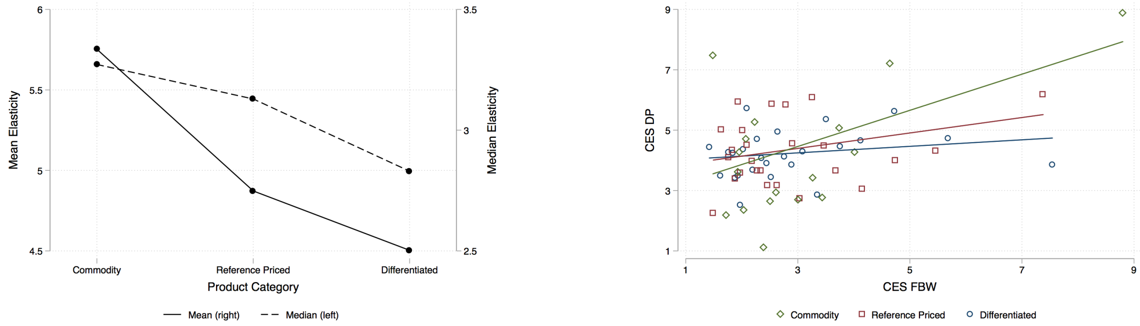
	HS10	SITC5	SITC3
Mean	5.65	5.09	4.49
(SE)	(0.09)	(0.21)	(0.40)
Median	3.37	3.13	2.87
(SE)	(0.05)	(0.10)	(0.23)
N	8508	1296	147
T-statistics		2.493	2.836
Pearson χ^2 p-value		0.043	0.025

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 classifications, "Liberal" and "Conservative", that only differ in a few products that can be classified in multiple ways. The left panel of Figure D.1 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,

[A4] 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 D.1: 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.

as expected. We can reject the hypothesis that the combined set of commodities and referenced priced goods have the same mean or median than differentiated products.[A5] Table D.2 reports the corresponding values and their standard errors for Figure D.1 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 conventional 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 average be closer to, and more correlated with, the conventional estimates. Consistently with this intuition, the right panel of Figure D.1 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.[A6] Figure D.2 shows that the qualitative pattern is robust to how products are grouped between homogenous and differentiated.

[A5] 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.

[A6] 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.

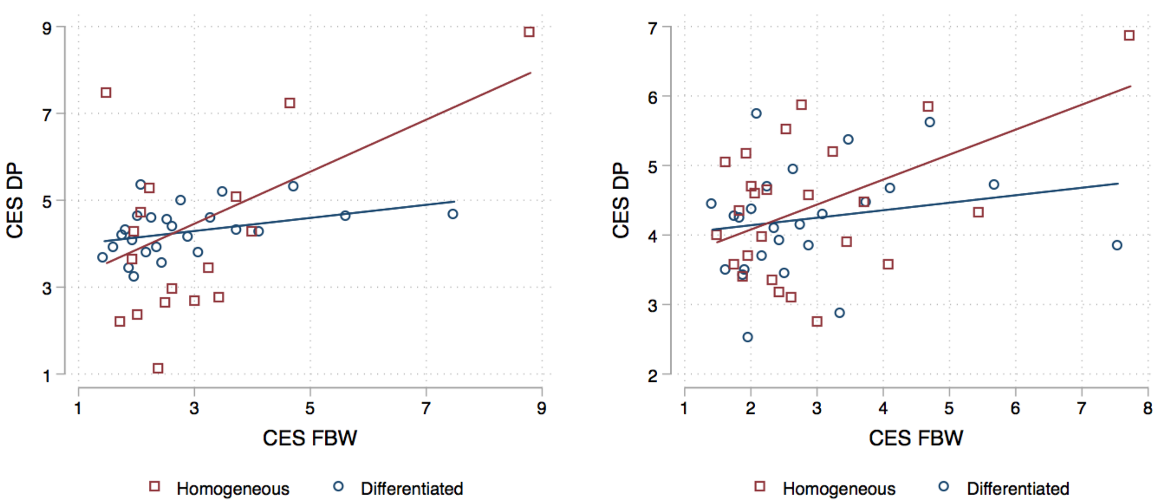
Table D.2: DP Estimates: Rauch Classifications

	Commodity	Reference Priced	Differentiated
Mean	5.75	4.87	4.50
(SE)	(0.86)	(0.42)	(0.25)
Median	3.27	3.13	2.83
(SE)	(0.69)	(0.18)	(0.18)
N	50	168	317

	Commodity	Reference Priced	Differentiated
Mean	5.28	4.77	4.58
(SE)	(0.63)	(0.42)	(0.27)
Median	3.24	3.10	2.82
(SE)	(0.37)	(0.18)	(0.21)
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 D.1 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 D.2: Correlation DP and FBW, Different Pooling of Rauch Categories



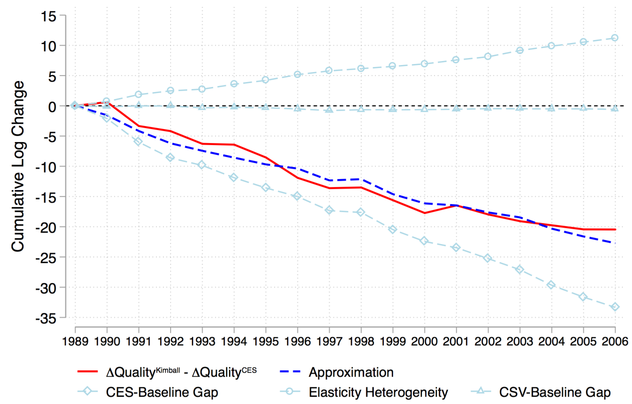
Note: The figure shows the correlation between the estimated elasticities using the DP and FBW methods at the SITC4 level using alternative breakdowns across products. Conservative Rauch classification is used. In the left panel, homogeneous products are defined as commodities only while, in the right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

D.2 Further Results on Welfare and Quality Decomposition

D.2.1 Bias in Inferred Quality: CES vs. Kimball

Proposition A.1 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 D.3: Quality Contribution: Kimball vs CES



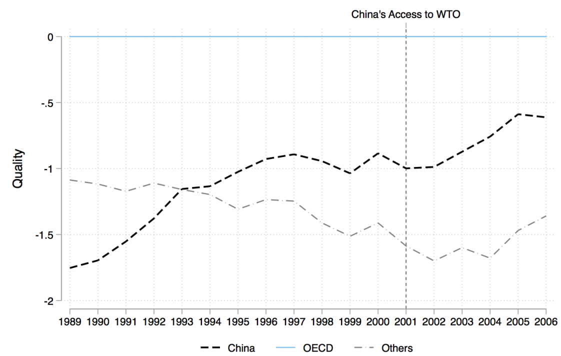
Note: The figure plots the decomposition of the gap in the Torqvist-weighted mean quality change between the inferred quality using Kimball and that under CES. The solid red line represents the estimate Kimball-CES gap in aggregate quality change. The dashed blue line represents the approximation of the gap according Proposition A.1. 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).

Figure D.3 shows the cumulative gap between Kimaball and CES and its decomposition into the the three components based on Proposition A.1. The contribution of the first term, the gap in the love-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).

D.2.2 Quality Decomposition

Figure D.4 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 D.4: 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 D.3 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.

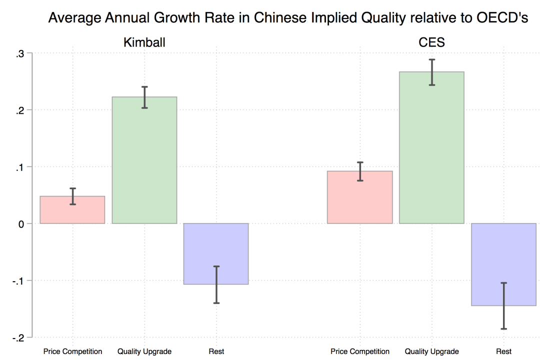
Table D.3: Between and Within Decomposition

	$\Delta\varphi$	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 E.1, 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 E.1. 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 specification 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).

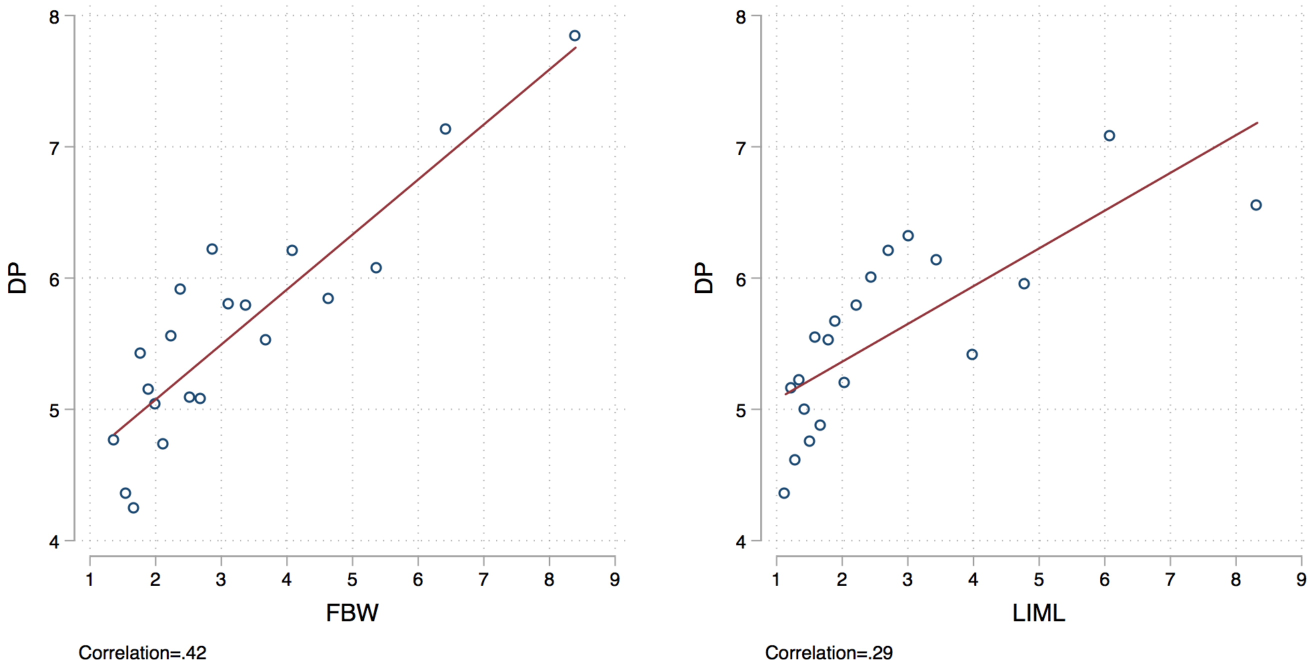
Figure D.5: Inferred Quality: Quality Upgrading and Price Competition



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 E.1.

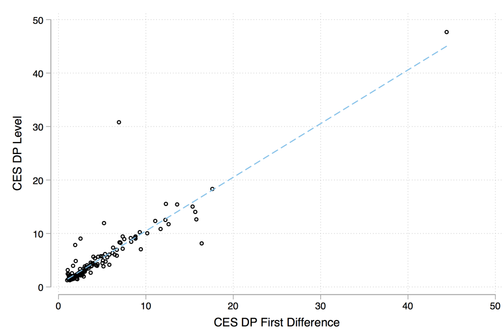
D.3 Additional Tables and Figures

Figure D.6: Correlation between DP and FBW or LIML Estimates, HS10 level



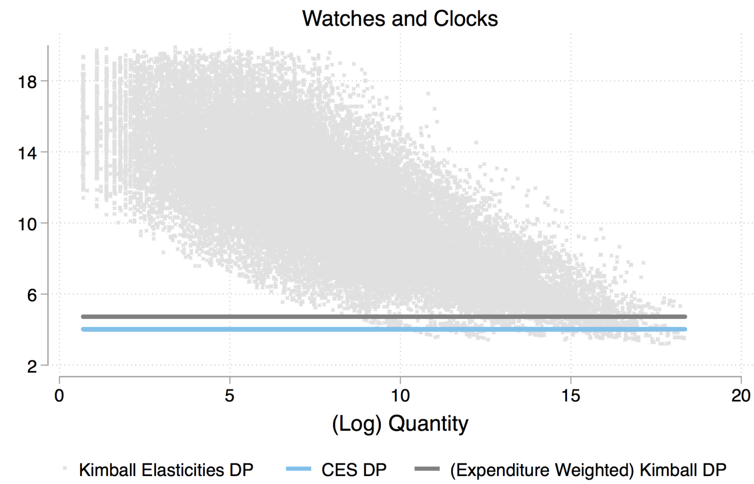
Note: The figure shows the binscatter plot of the relationship between the estimated elasticities using the DP approach and conventional methods like FBW (right panel) and LIML (left panel). The figures refers to the set of estimates at the HS10 level. Elasticities are censored at 10.

Figure D.7: 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 D.1. Dashed line represents the 45 degrees line.

Figure D.8: CES-Kimball Elasticity: Watch and Clocks



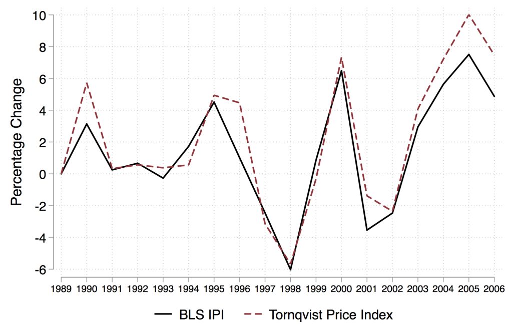
Note: The figure shows the entire set of Kimball price elasticities of each variety-time pair, σ_{it}, as a function of the (log) quantity imported for the sector Watches and Clocks (SITC3 884). The gray line represents the expenditure-weighted mean Kimball price elasticity while the blue line represents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

Table D.4: Kimball Parameters

	σ	σ_o	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)

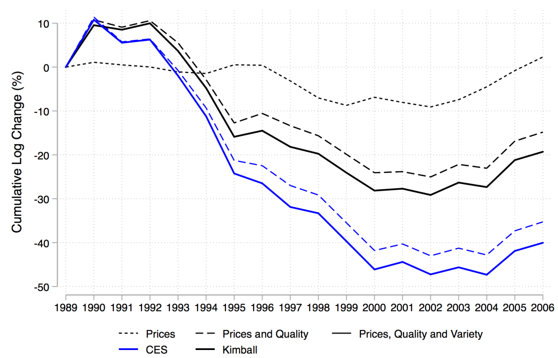
Note: The table displays the mean and the median across all SITC3, with the corresponding standard errors, of the estimated parameters of the Finite-Finite Kimball specification.

Figure D.9: 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 D.10: Dynamics of US Import Price Index - PPI Deflated



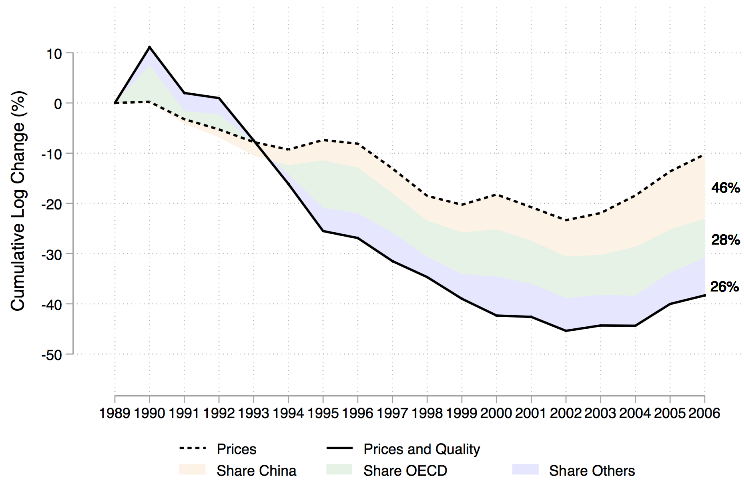
Note: The figure plots the aggregate import price indices for both the CES and the Kimball specifications and their decomposition into the price, quality and variety components, according Equations (19) and (23). Prices are deflated using the PPI index from BLS. The measure of inferred quality is normalized 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 D.5: 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 (??) and (??) and reported in Figure D.10, 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 D.11: Price Index, Decomposition of Quality across Countries: CES case



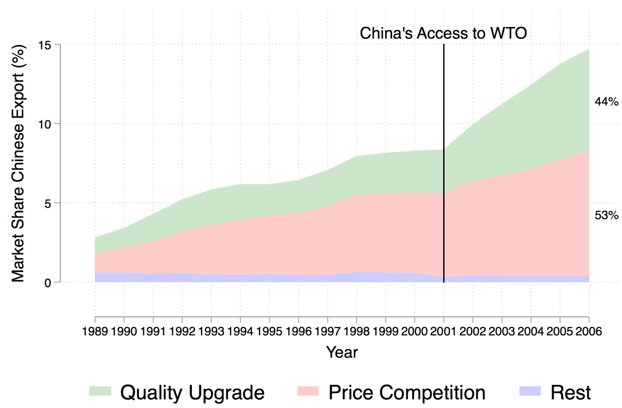
Note: The dashed line figure shows the price component of the aggregate import price index. The solid line shows the price component and the quality component of the aggregate import price index. The quality contribution is computed using the inferred quality from the CES specification. The difference 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).

E Additional Tables and Figure

E.1 Examining the Share of China in US Imports

Figure E.1 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), which represent 44% of the value of Chinese imports to the US by the end of this period.

Figure E.1: Decomposition of Chinese Export: Quality Upgrade and Price Competition

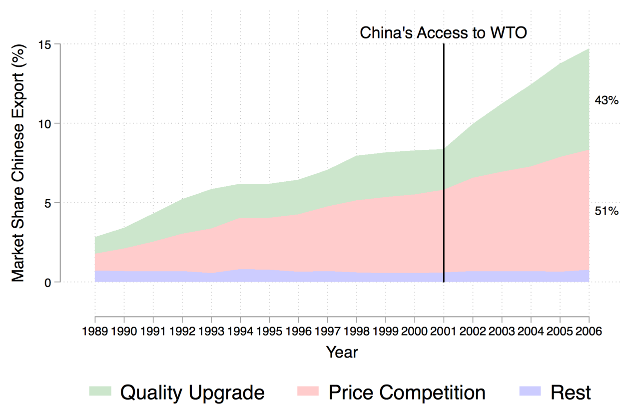


Note: The figure shows the decomposition of Chinese import share into three categories: Quality Upgrade, Price Competition and Rest. Quality Upgrade represents the market share of Chinese products whose both market share and relative price increased over time on average. Price Competition includes those 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 E.1 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 E.3 and Table E.3 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 E.1 shows that most of the growth due to quality upgrade took place after China's access to WTO in 2001.

Figure E.2: 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 E.1: 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 E.3: 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 E.2: 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 E.3: 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.