# Mergers, Foreign Competition, and Jobs: Evidence from the U.S. Appliance Industry

Felix Montag
NYU Stern, CEPR*

This version: April 30, 2026

**Abstract**

Policy choices often create trade-offs between workers and consumers. I examine how foreign competition alters the consumer welfare and domestic employment effects of mergers. I construct a model incorporating consumer demand, endogenous product portfolios, and employment decisions. Applying the model to Whirlpool's acquisition of Maytag in the appliance industry, I compare the observed merger to a counterfactual acquisition by a foreign buyer. Although Whirlpool's acquisition decreased consumer welfare by $271 million annually, it preserved 797 domestic jobs. These jobs must therefore be valued at more than $344,000 per year for the domestic employment benefits to offset the consumer harm.

**JEL classification: F61, L13, L40**

*Email: felix.montag@nyu.edu. I am deeply grateful to my advisors Monika Schnitzer and Ali Yurukoglu for their patient guidance, constant encouragement, and invaluable advice. I thank Alessandra Allocca, Antonin Bergeaud, Laura Grigolon, Anna Gumpert, Ying Fan, Teresa Fort, Mitsuru Igami, Torsten Jaccard, Claudia Steinwender, Fabian Waldinger, Lulu Wang, Martin Watzinger, and participants at many seminars and conferences for helpful comments and discussions. I am grateful to Boyang Zhang for excellent research assistance. Financial support from the German Research Foundation (DFG) through CRC/TRR190 (project number 280092119) and the International Doctoral Program "Evidence-Based Economics" of the Elite Network of Bavaria is gratefully acknowledged. This work was supported in part through the NYU IT High Performance Computing resources, services, and staff expertise.

# 1 Introduction

Mergers can have significant employment effects, potentially creating a trade-off between competition and jobs.[1] While competition authorities typically focus on consumer outcomes, employment impacts remain understudied and the explicit trade-off rarely evaluated.[2] This analysis is particularly relevant when firms face foreign competition, since blocking mergers might lead to aggregate employment losses.[3]

In this paper, I specify and estimate a structural model of demand and supply to study how foreign competition affects a merger's consumer welfare and employment outcomes. I incorporate two key firm responses: price adjustments and product portfolio decisions. To capture the effects of product entry and exit on consumers and employment, I embed consumer demand into an endogenous product-choice model, where domestic labor demand depends on production locations and equilibrium product market quantities. My key methodological innovation is to construct a model that captures the interactions between the product market and labor demand. Using this framework, I estimate the average domestic job value at which employment gains offset consumer losses.

To illustrate this worker–consumer trade-off, I use the model to study the landmark Whirlpool–Maytag merger in the U.S. appliance market. I simulate consumer welfare and employment effects under two scenarios: the actual acquisition of Maytag by Whirlpool and a hypothetical acquisition by the alternative bidder at the time, the Chinese firm Haier. For tractability, production locations are treated as exogenous. In the Whirlpool scenario, I use observed post-merger locations; for Haier, I assume complete offshoring of Maytag's production to China.[4] Although an acquisition by Haier posed no direct threat to consumers (having no prior U.S. presence), its offshoring plans risked greater U.S. job losses.

Three main findings emerge. First, the Whirlpool acquisition is always worse for consumers. The merging parties increase prices without triggering significant rival product entry, causing an annual consumer welfare loss of $271 million. Second, Whirlpool preserves

[1]Examples include proposed mergers between PSA and Fiat Chrysler (FCA), T-Mobile and Sprint, Albertsons and Kroger, or U.S. Steel and Nippon Steel.

[2]A nascent literature studies labor market power arising from overlaps in local labor markets (Prager and Schmitt, 2021; Shapiro, 2019; Marinescu and Hovenkamp, 2019). By contrast, I examine employment effects absent such overlaps.

[3]Many jurisdictions (e.g., Australia, China, France, Germany, Italy, Korea, the United Kingdom, South Africa) explicitly consider public interest in merger control (OECD, 2016). While the European Union and the United States currently do not, worker interests have become increasingly prominent in merger control in these jurisdictions.

[4]This assumption follows anecdotal evidence about Haier's bid, detailed in Section 2.

approximately 797 more U.S. jobs than Haier would have. Finally, each additional job preserved by Whirlpool (relative to a Haier acquisition) must be valued at about $344,000 annually to offset consumer losses.

While the worker–consumer trade-off in this application strongly depends on an alternative buyer's offshoring plans, such a trade-off can arise more generally.[5] Given sufficient information on counterfactual plant locations, the methodology outlined here can be applied to any merger or policy involving a worker–consumer trade-off.

The counterfactual simulations demonstrate that incorporating pricing and product assortment decisions significantly alters estimated employment effects, with important implications for studies of multinational enterprises (MNEs).[6] Focusing on a single industry clarifies the trade-offs MNEs face in their global production decisions. In appliances, MNEs produce distinct product groups in different locations. Due to the oligopolistic market structure, cost changes at one location lead to adjustment of prices, product portfolios, and labor demand across locations for the affected firm and its rivals. This complements Muendler and Becker (2010), who analyze how employment at MNEs adjusts at both extensive (opening a new foreign location) and intensive margin (changing employment at an existing location) when different locations can complement or substitute each other's production. While I focus only on intensive-margin adjustments, I explicitly model equilibrium effects following cost changes at particular locations. The results also complement Igami (2018), who studies the interplay between offshoring and market structure without employment implications.

For the empirical analysis, I assemble a comprehensive data set for U.S. residential laundry machines between 2005 and 2015. The core of the data comes from *TraQline*, a representative survey of 600,000 households per year. On the production side, I hand-collect product-level data on the locations of plants manufacturing for the U.S. market.

Using a difference-in-differences strategy similar to Ashenfelter, Hosken, and Weinberg (2013), I document trends around Whirlpool's acquisition of Maytag. Post-merger, U.S. market concentration rose significantly. Prices remained stable but fell in Europe, where Maytag was absent. Foreign rivals offered more products post-merger, but this was also the case in Europe. Finally, local unemployment increased following Maytag plant closures.

The descriptive evidence raises several questions. Was the expansion of rival product portfolios induced by the merger? Was consumer harm by the Whirlpool acquisition offset by benefits to U.S. workers? Answering these questions requires a model.

The model has two stages and features manufacturers and consumers. Manufacturers

[5]For example, Stellantis CEO Carlos Tavares argued the FCA–PSA merger into Stellantis would improve competitiveness and prevent job losses (Noble, 2021).

[6]For example, see Tintelnot (2017) or Arkolakis, Eckert, and Shi (2023).

first choose product portfolios from technologically feasible options at fixed costs and hire workers.[7] These decisions are based on expectations about second-stage sales and profits. Each product is associated with an exogenous set of characteristics, a production location, and a marginal cost of production. Whether a job is created domestically or abroad depends on the production location for each product. In the second stage, firms set prices, and consumers make purchases. Consumer demand follows a random coefficients discrete-choice model with income-dependent price sensitivity and heterogeneous tastes for front-loading washers, estimated following Berry, Levinsohn, and Pakes (2004). Identification exploits household-level income and price variation, second-choice characteristics, and an instrumental variable (IV) based on production locations and real exchange rates (RER), which is exogenous to product-level demand conditions (Goldberg and Verboven, 2001; Grieco, Murry, and Yurukoglu, 2024).

On the supply side, I estimate marginal costs assuming differentiated Bertrand-Nash competition. Fixed cost bounds for product offerings are estimated via moment inequalities, similar to Pakes et al. (2015) and methodologically closest to Eizenberg (2014). Intuitively, the fixed cost of offering a product that was offered can at most be the change in the expected variable profit due to the product. Similarly, the fixed cost of offering a product that is part of the set of potential products but was not offered must be at least as high as the change in variable profit due to the removal of that product.

I collect plant-level data to estimate the relationship between employment and output using a Leontief production function. I find that after a fixed employment threshold, output rises linearly with additional labor. Combined with the product-level plant locations, I can estimate how different product market equilibria affect the demand for domestic manufacturing workers. Furthermore,, I estimate how marginal costs vary with proxies for labor and transportation costs to compute how marginal costs react to changes in production locations.

Identifying the potential product sets for multiproduct firms is an empirical challenge.[8] I overcome this issue by exploiting an unconditionally cleared merger, where I observe the state of the world where the incentive for rivals to offer more products is greatest. Draganska, Mazzeo, and Seim (2009) and Fan and Yang (2025) instead exploit cross-sectional variation. This is infeasible in my setting because portfolio decisions are national.

A second empirical challenge is equilibrium multiplicity for the counterfactual portfolio choice. Due to the large number of products, computing all potential equilibria is computationally infeasible. Instead, I follow a literature that uses heuristic learning algorithms

[7]Since I observe only product-level entry but no firm-level entry around the time of the merger, I focus on endogenous product choices and abstract from firm entry.

[8]An earlier literature on endogenous product entry focuses on single-product firms with discrete product types (Mazzeo, 2002; Seim, 2006).

to determine equilibrium portfolios (Lee and Pakes, 2009; Wollmann, 2018; Fan and Yang, 2020). Each player optimizes her portfolio sequentially, taking the choices of rivals as given, until there is no profitable one-step deviation.

The simulation results indicate that each job preserved under an acquisition by Whirlpool (relative to Haier) would need to have an annual average value of at least $344,000 to offset the associated consumer harm ($238,000 if we consider the sum of consumer welfare and industry profits). By contrast, Flaaen, Hortaçsu, and Tintelnot (2020) find that each job created by the 2018 washing machine tariffs was associated with an annual consumer harm of $800,000. Furthermore, Setzler and Tintelnot (2021) find an annual local wage bill gain of $113,000 per job created by foreign MNEs, excluding other employment benefits. Employment impacts are substantial and unevenly distributed. Whereas the losses to consumers are spread across the country, the employment effects are concentrated in a few local labor markets. While the gains from procompetitive competition enforcement likely outweigh losses, the results suggest that pairing it with complementary labor policies like wage insurance under the Trade Adjustment Assistance Program (Hyman, Kovak, and Leive, 2023) could increase its popular support.

Finally, I provide novel evidence that endogenous product portfolio decisions intensify consumer harm from mergers.[9] Although product entry was key to the clearing decision for the Whirlpool–Maytag merger, I find that endogenous portfolio adjustments increase the harm to consumers. This is because the rival product portfolio expansion is mostly independent of the merger whereas the merging parties offer fewer products post-merger. Existing studies mostly consider hypothetical concentration changes and find mixed results.[10] Under certain conditions, Caradonna, Miller, and Sheu (2025) show that without marginal cost efficiencies, product portfolio adjustments can only be profitable for the parties if there is harm to consumers.

The remainder is structured as follows: Section 2 describes the case and data, Section 3 provides descriptive evidence, Section 4 details the model, Section 5 describes estimation, Section 6 presents results, Section 7 describes welfare implications, and Section 8 concludes.

[9] Related work studies static entry for single-product firms (e.g., Li et al., 2022, Ciliberto, Murry, and Tamer, 2021), dynamic multiproduct entry (Garrido, 2020), post-merger repositioning (Fan, 2013), and merger impacts on radio station variety (Berry and Waldfogel, 2001; Sweeting, 2010; Jeziorski, 2015).

[10] Fan and Yang (2020) find that endogenous product adjustments exacerbate negative consumer welfare effects, while Wollmann (2018) finds the opposite. Fan and Yang (2025) show that product portfolio adjustments exacerbate negative merger effects in small markets and reduce consumer harm in larger markets.

# 2 Institutional Setting and Data

In the mid-2000s, around 90 percent of washing machines sold in the U.S. were produced by the U.S. manufacturers Whirlpool, Maytag, and General Electric, which mostly produced domestically. While the Swedish Electrolux also manufactured in the U.S., LG and Samsung entered the market from plants in Mexico and South Korea.

## 2.1 Whirlpool's acquisition of Maytag

Before its acquisition by Whirlpool, Maytag struggled financially despite workforce reductions and reported a net loss in 2004 (Maytag, 2005). In May 2005, it initially agreed to a private investor buyout for $1.1 billion (Barboza, 2005). Haier, a Chinese manufacturer, made a competing $1.3 billion bid in June 2005, but Whirlpool outbid it in July 2005 with $1.4 billion. On March 31 2006, Whirlpool acquired Maytag after receiving an unconditional merger clearance from the Department of Justice (DoJ).

Haier's bid aligned with China's "Go Out Policy", encouraging overseas acquisitions to obtain access to foreign markets, particularly in the European Union and the United States, for Chinese manufactured goods (Goodman and White, 2005). Since Chinese acquirers were met with resistance, these acquisitions often targeted well-known brand names slipping into decline. Maytag, with declining performance but strong brands, suited this strategy. Haier aimed to offshore production to China, using Maytag's distribution channels and brand reputation (Goodman and White, 2005).

Whirlpool's bid prevented a foreign takeover but raised competitive concerns. The DoJ's investigation focused on residential washing machines and dryers.[11] The DoJ cleared the merger despite high concentration, expecting foreign entrants like LG and Samsung to prevent price increases (Department of Justice, 2006). Baker and Shapiro (2008a) call this decision "[...] a highly visible instance of underenforcement", and Baker and Shapiro (2008b) describe it as "fueling the perception that the Justice Department has adopted a very lax merger enforcement policy [...]". They conclude that, in this case, the DoJ was willing to accept entry and expansion arguments in a highly concentrated merger case despite the fact that entrants had thus far achieved only relatively low market shares.

## 2.2 Data

To analyze the implications of the Maytag acquisition, I construct a comprehensive data set on the U.S. market for residential laundry products between 2005 and 2015.

[11] See Armington, Emch, and Heyer (2006) for a case description from the perspective of the DoJ.

### 2.2.1 Sales, products, and households

The main data source, *TraQline*, is an annual survey of 600,000 U.S. households on appliance purchases, capturing product characteristics, prices, second-choice brands, retailers, and household demographics for which I have data for 2005–2015. The data set is well known across the appliance industry and is used by retailers and brands in the industry as a source for market insights.[12] The data include information for washers and dryers and for freestanding ranges. I aggregate responses nationally and annually.

While *TraQline* records characteristics, respondents are not asked to provide the exact model specification. I therefore define a product as a brand, retailer, and key characteristic combination. Most brand owners use different brands to cluster their product offering according to the preferences of the consumers that they target.[13] Thus, the brand of a product already captures much of the variation in (otherwise unobserved) product differentiation. The key characteristic for washers is whether it is a regular top loader (with an agitator), a high-efficiency top loader (without an agitator) or a front loader. Finally, I refine the product definition by using information on the retailer at which the product is sold.[14]

Households also need to report other characteristics of their purchases. For washers, these include child lockout features, the number of programs, or noise insulation. For each product, I calculate the average value of these characteristics among the subsample of respondents. I enrich these data with brand-level repair rates from Consumer Reports and advertising expenditures from Kantar AdSpender (Benkard, Yurukoglu, and Zhang, 2021).

I draw a random sample of households from the IPUMS Current Population Survey (CPS) to have data on the unconditional distribution of income in the population. I need this to identify how household income affects the sensitivity to prices in the demand estimation.

In the descriptive analysis, monthly data on model-level washing machine sales for Germany, France, Great Britain, and the Netherlands between 2005 and 2008 from *Gesellschaft für Konsumforschung* provide a control group for markets unaffected by the merger.

[12]The only other comparable source of data on volume and value sales in the appliance industry is a (now discontinued) retailer panel by the NPD Group, which is the basis of the analysis by Ashenfelter, Hosken, and Weinberg (2013).

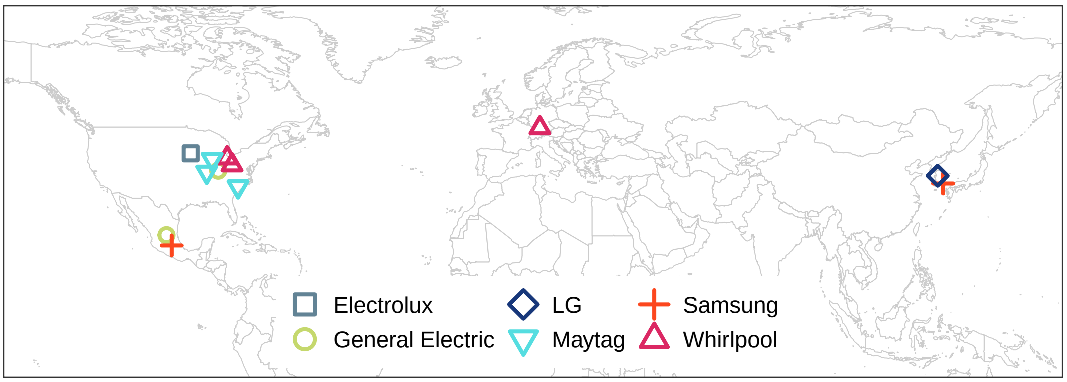
[13]In its 2007 annual report, Whirlpool describes what each of its brands represents and what type of consumers it targets. Amana, for example, is described as stylish and affordable, whereas KitchenAid stands for quality and craftsmanship, Whirlpool for innovation and Maytag for reliability.

[14]For retailers, I distinguish Best Buy, H.H. Gregg, Home Depot, Lowe's, Sears, and all others. The latter group predominantly includes smaller, regional retailers.

## 2.3 Production locations, cost shifters and employment

I hand-collect product-level manufacturing locations for washing machines for the U.S. market. Figure 1 shows the plant locations of major washing machine manufacturers in 2005. Details on the construction of this data set and the weights on the share of the products produced in each production location are described in Appendix I.B.

**Figure 1:** Washing machine plants manufacturing for the U.S. market, 2005




*Notes:* The map shows all plants manufacturing washing machines for the U.S. market in 2005 by manufacturers with a market share of more than 3 percent in any year in the sample. The appendix includes a map for 2007 in Figure A.4, for 2009 in Figure A.5 and for 2011 in Figure A.6.

Pre-merger, Maytag production was entirely domestic, whereas Whirlpool's top loaders were produced in the U.S. and most front loaders in Germany. Post-merger, Whirlpool restructured Maytag operations. Although it maintained some of Maytag's manufacturing plants for other appliances (e.g. in Amana, Iowa, or Cleveland, Tennessee), it shut down laundry plants in Searcy, Arkansas (700 manufacturing jobs) and Herrin, Illinois (1,000 manufacturing jobs), as well as the laundry manufacturing and headquarter operations in Newton, Iowa (1,000 manufacturing and 1,800 corporate jobs).[15] At the same time, Whirlpool announced adding a total of 1,500 jobs at an existing top loader plant in Clyde, Ohio and an existing dryer plant in Marion, Ohio. The production of Maytag front loaders, as well as new Whirlpool front loader models, moved to a production facility in Monterrey, Mexico.[16]

I construct a product-level cost shifter using the product-level weighted average real exchange rate between the U.S. and the countries in which the product is produced. The RER comes from the Penn World Table. Product-level plant weights are based on the share of a product produced in a particular origin country in a given year. I use the RER based

[15] According to Maytag (2005), the company employed around 13,500 in its household appliance operations in the U.S.

[16] Moving Whirlpool front loader production to the Monterrey plant is not merger-specific, as Whirlpool announced eventually moving its front loader production for the U.S. to Monterrey in 2003 already.

on consumption expenditures. I calculate this by dividing the consumption of households at nominal prices by the the same consumption using the U.S. price level in 2005 and then multiplying this by the nominal exchange rate between the local currency and the U.S. dollar (Feenstra, Inklaar, and Timmer, 2015). The measure captures differences in relative price levels and serves as a proxy for local wage levels and nominal exchange rate fluctuations. Figure A.7 in Appendix I.C shows the evolution of the average RER over time and illustrates the source of the variation.

Estimating the relationship between plant-level output and employment requires plant-level data on both. Since these data are only sparsely available for plants producing for the U.S., I also consider BSH and Whirlpool plants that produce for the European market. In practice, the technology at a Whirlpool plant producing washing machines for the U.S. market in Germany appears to be similar to the technology at a Whirlpool plant producing washing machines for the European market. I collect data on annual plant output quantities and manufacturing workers employed between 1995 and 2017. In total, there are 25 plant–year combinations. Four of these belong to Whirlpool plants producing for the U.S. market, whereas 21 belong to BSH and Whirlpool plants producing for the European market. Details on the construction of this data set are described in Appendix I.B.

## 2.4 Labor market data

To analyze the local labor market impacts of plant closures or employment increases at existing plants, I use wage and employment data from the Quarterly Census of Employment and Wages (QCEW) which includes quarterly county-level employment and compensation. I use the wages per employee and number of persons employed, disaggregated by county and industry. The wages include total compensation, bonuses, stock options, severance payments, the cash value of meals and lodging, tips, and other gratuities. I annualize these wages to ease interpretation. Unemployment data are drawn from Local Area Unemployment Statistics (LAUS). I construct matched control counties based on industry composition, demographics, and educational attainment. The industry composition is available annually in the QCEW, which I use for 2003 to 2006. The American Community Suvey (ACS) is not available at an annual frequency, which is why I use the 2005–2009 average as information on demographics and educational attainment from the 2009 ACS.

**Table 1:** Volume share by brand owner (%)

| | Clothes washers | | | Clothes dryers | | |
|---|---|---|---|---|---|---|
| | 2005 | 2007 | 2009 | 2005 | 2007 | 2009 |
| Whirlpool | 25 | 44 | 42 | 26 | 44 | 42 |
| Maytag | 23 | | | 21 | | |
| Sears | 25 | 20 | 18 | 25 | 21 | 19 |
| General Electric | 14 | 17 | 16 | 15 | 17 | 16 |
| Electrolux | 7 | 6 | 6 | 7 | 6 | 5 |
| LG | 3 | 7 | 10 | 2 | 6 | 10 |
| Samsung | 0 | 1 | 4 | 0 | 1 | 4 |
| HHI | 2,036 | 2,708 | 2,496 | 2,068 | 2,773 | 2,500 |
| ΔHHI | | 1,147 | | | 1,125 | |

*Notes:* The table reports volume-based market shares by brand owner for washers and dryers pre-merger (2005) and post-merger (2007, 2009). The HHI is calculated as the sum of squared market shares in whole percentages. The increase in HHI is computed using pre-merger market shares.

# 3 Descriptive Evidence

Before presenting the theoretical model, I describe concentration, prices, entry, and employment trends around the Maytag acquisition.

## 3.1 Changes in concentration

Table 1 shows brand owner market shares around the merger. Whirlpool and Maytag were previously the top domestic manufacturers, since Sears does not manufacture any appliances. Haier had no U.S. market presence.

The pre-merger Herfindahl–Hirschman index (HHI) and the post-merger increase indicate significant competitive concerns under U.S. merger guidelines.[17]

Due to data limitations, I focus on washers from hereon after. Whereas I have access to detailed sales data for washing machine markets unaffected by the merger, I do not have comparable data for dryers. Similarly, I collect detailed information on the production locations of washers, whereas this is more difficult for dryers. On the product market side, the results can be expected to be similar. As shown in Table 1, market shares for washers and dryers evolve similarly. In Appendix II, I show that some of the descriptive evidence for

[17]The HHI is calculated as the sum of squared market shares in whole percentages. According to the 2023 U.S. horizontal merger guidelines, markets with an HHI greater than 1,800 are considered highly concentrated. In such markets, an HHI increase of more than 100 is presumed to substantially lessen competition.

price effects and entry by LG and Samsung is similar for washers and dryers.

## 3.2 Evolution of prices

To assess merger-related price changes, I compare the logarithm of washer prices in the affected U.S. market to unaffected European markets.[18] As Maytag had no significant presence in Europe, the latter serve as an appropriate control group subject to similar industry trends but unaffected by the merger.

I use quarterly data for the years 2005–2008 to estimate a separate event study for every country. Specifically, I estimate the parameters of the following model:

$$ln(p_{it}) = \beta x_{it} + \delta_{b(i)} + \gamma_t + \epsilon_{it} \, , \tag{1}$$

where $i$ denotes a model of brand $b$ at time $t$, $x_{it}$ are product characteristics, $\delta_{b(i)}$ are brand fixed effects, $\gamma_t$ are quarterly time fixed effects, and $\epsilon_{it}$ are idiosyncratic product-level shocks. Product characteristics differ slightly by country, but generally include washer type and performance features. Standard errors are clustered at the model level.

Figure 2 plots the residualized price evolution. Q1 of 2006, the quarter prior to which Whirlpool acquired Maytag, is normalized to zero. The merging parties reported that the integration process should take up to a year, which is why we should expect to see price effects of the merger from 2007 onwards.

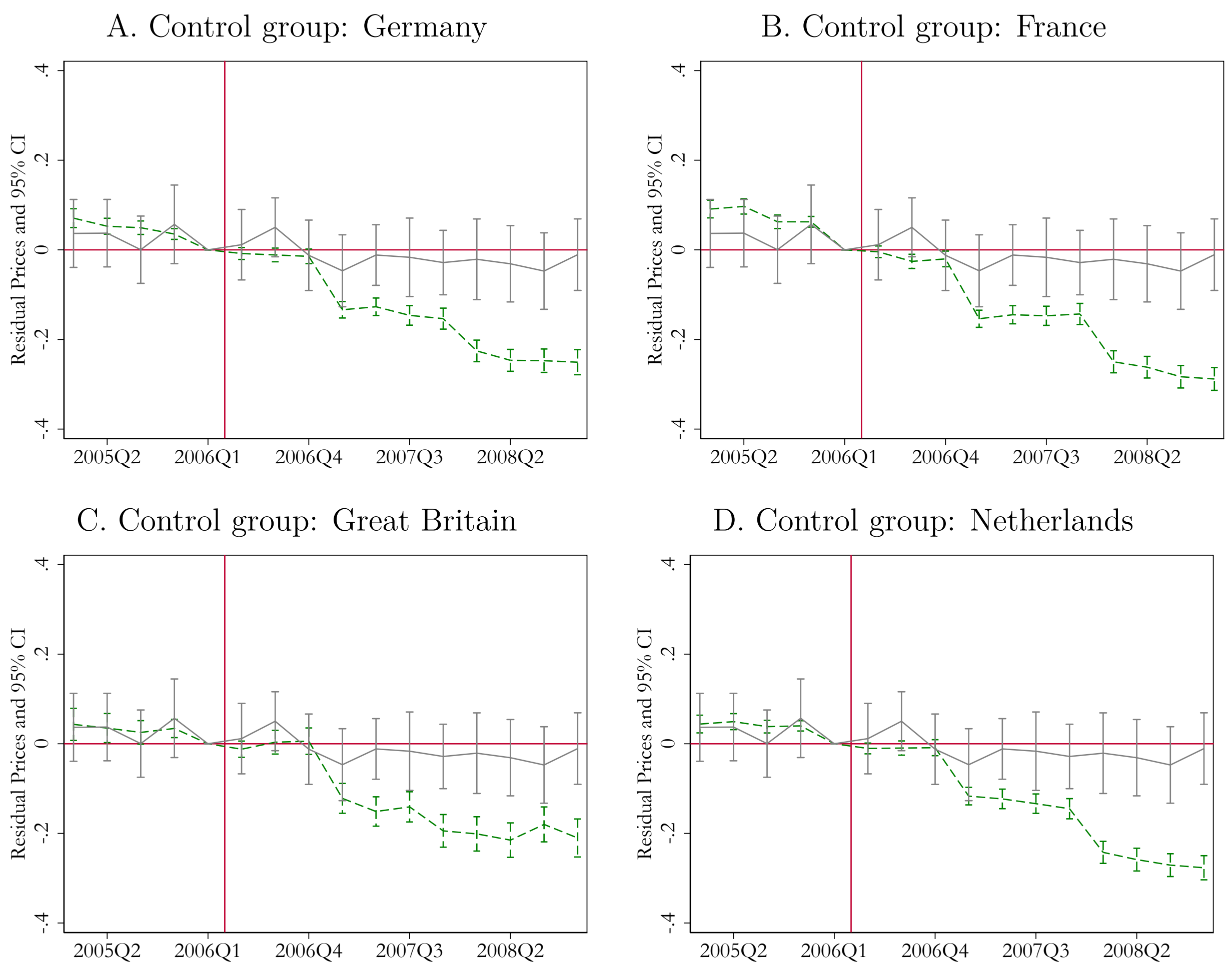
Prices in the U.S. and Europe tracked similarly pre-merger. Post-merger, European prices declined while U.S. prices remained stable. If the washing machine markets in the control countries are subject to similar industry trends on all aspects other than the merger, this suggests that the Maytag acquisition by Whirlpool significantly increased prices relative to their counterfactual evolution.[19]

Studying the price evolution in the U.S. without a control market, one might incorrectly conclude that the merger did not lead to price increases. However, this would miss cost decreases in the industry during the 2000s caused by a global trend to relocate production to low-cost countries. As shown in Figure A.7, most major manufacturers (including Whirlpool) relocated increasing shares of their production to lower-cost countries between 2007 and

[18] Ashenfelter, Hosken, and Weinberg (2013) follow an alternative strategy by comparing prices to those of unaffected control products, incl. ranges. I replicate their analysis using the TraQline data in Appendix II. In contrast to my results, they find no price effects of the merger for washers. I believe that relying on washer prices in unaffected market is a better control group because they are unaffected by the merger but are otherwise affected by similar demand and supply shocks.

[19] In Appendix Figure A.9, I plot the evolution of deflated consumer price indices in the U.S. and EU between 2001 and 2015. The results corroborate the findings of the descriptive price analysis using GfK data.

**Figure 2:** Price effects of the merger for washing machines




*Notes:* The figure displays the residualized log prices for Maytag and Whirlpool washing machines in the U.S. relative to washers from manufacturers in control countries unaffected by the merger. The merger occurred at the end of 2006Q1, normalized to zero. The solid line represents the U.S.; the dashed line represents the control group. Confidence intervals are at the 95% level, with standard errors clustered at the model level.

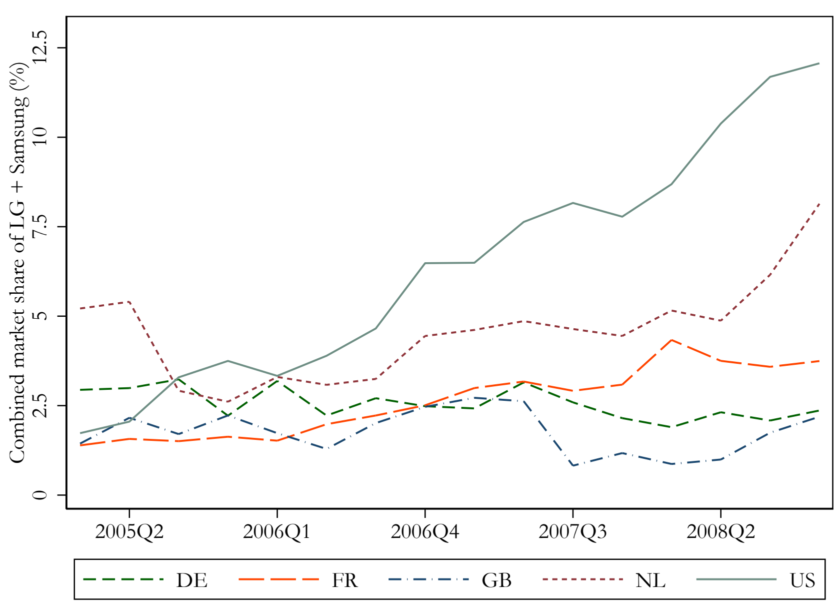
2010.[20] Another explanation for price decreases in Europe is entry by new competitors from Asia (e.g., LG and Samsung), which occurred around the time of the merger.

## 3.3 Product entry

To assess the effects of the merger on consumers and workers, I need to understand whether rival product entry would have occurred even in the absence of the merger. Rival product entry could affect the estimated price effects of the merger in two distinct ways. First, if the merger led to merger-specific product entry, this could increase competition and decrease prices. Second, if there was merger-independent product entry by rivals around the time of the merger, this would also increase competition and reduce prices.

Figure 3 compares market shares of LG and Samsung in the U.S. versus several European markets. Both firms were active across all markets before the merger. Their combined share stagnated in Germany and Great Britain, while increasing in France, the Netherlands, and especially the U.S. This indicates that LG and Samsung's U.S. expansion was likely not solely driven by the merger, though stronger U.S. growth raises the possibility of merger-induced entry.

**Figure 3:** Combined market share of LG and Samsung in the U.S. and Europe




*Notes*: The figure shows the combined market share (volume sales) evolution in the U.S. and key European control markets from 2005 to 2008.

[20] Appendix I.C documents quotes from the annual reports of, e.g., Electrolux and Maytag, to show that this was a key part of their business strategy at that time.

In Appendix II, I document similar patterns for washers and dryers, highlighting minimal expansion by LG and Samsung in freestanding ranges, suggesting limited appropriateness of ranges as a control group.

## 3.4 Labor market effects of the acquisition

The analysis so far focused on the product market effects of the acquisition. Different acquisitions may also entail different changes to employment. For those to enter the overall welfare effects, appliance manufacturing jobs need to matter for local labor markets. In the following, I assess how the Maytag plant closures by Whirlpool post-acquisition affected employment, unemployment, and wages of the employed in the affected counties.

Although Whirlpool maintained some of Maytag's manufacturing plants (e.g., in Amana, Iowa, and Cleveland, Tennessee), shortly after the acquisition, it shut down appliance manufacturing plants in Searcy, Arkansas (700 manufacturing jobs) and Herrin, Illinois (1,000 manufacturing jobs), and manufacturing and headquarters operations in Newton, Iowa (1,000 manufacturing and 1,800 corporate jobs). At the same time, Whirlpool announced the addition of 1,500 jobs at two existing plants in Ohio. There were thus three mass layoffs and two new job events. All of these were announced in 2006 and occurred in 2007.

To quantitatively assess employment impacts from Maytag plant closures following Whirlpool's acquisition, I use an event-study methodology inspired by Gathmann, Helm, and Schönberg (2020). I compare labor outcomes in treated counties to those in a set of matched control counties using an event study methodology.

I match a control group for every treated county that is similar on pre-treatment industry composition (21 different industries), as well as age structure (age groups 15–24, 25–49, and 50–66), education (low, medium, and high), and race (White, Black, and any other race). I do not match on any of the outcome variables of the employment analysis. Since I observe only a small number of events, I use the ten closest counties as a control group for every treated county instead of only the closest. Specifically, I calculate the normalized squared distance in the population share by characteristic of the treated counties to any other county in the United States.[21] For the industry composition, I use annual data for the four years prior to treatment (i.e., 2003–2006), since annual county-level demographic characteristics are not available.

[21] The distance equation for all treatment counties $i$ and control counties $j$ is given by $distance_{ij} = \sum_n \omega_n \sum_t \frac{(x_{int}-x_{jnt})^2}{s_{nj}^2}$, where $s_{nj}$ is the standard deviation of characteristic $n$ in the control counties $j$ and $\omega_n$ is the weights of the different characteristics. Industry composition together has a weight of 50 percent, and each of the demographic characteristics accounts for a third of the rest. See Gathmann, Helm, and Schönberg (2020) for more details on the methodology.

Next, I estimate the following event study:

$$\mathrm{Y}_{ct} = \sum_{\tau=2002}^{2006} \alpha_\tau \mathrm{Event}_{ct}^{\tau} + \sum_{\tau=2007}^{2008} \beta_\tau \mathrm{Event}_{ct}^{\tau} + \delta_c + \gamma_t + \epsilon_{ct}\,, \tag{2}$$

where $Y_{ct}$ is the logarithm of unemployment, manufacturing employment or annualized manufacturing wages in county $c$ at time $t$, $\mathrm{Event}_{ct}^{\tau}$ is an indicator equal to one if time $t$ is in year $\tau$ and county $c$ is a treatment county, $\delta_c$ is county fixed effects and $\gamma_t$ is time fixed effects. Whereas data on unemployment are available at monthly level, the other outcome variables are available only at quarterly level. In each case, I use the most disaggregated level.

In the baseline specification, I use a simple difference-in-differences strategy, where I use data for 2002–2006 as the pre-treatment period and data for 2007 and 2008 as the post-treatment period.[22] Appendix II includes graphical results for the full event study analysis, where there are separate quarterly treatment effects for the years prior to treatment (2002–2006) and the treatment years 2007 and 2008.

I group the counties into two different treatment groups and estimate separate regressions. The first treatment group consists of Jasper County, in which there was a shutdown of both manufacturing and corporate operations, as well as White and Williamson Counties, in which manufacturing plants were shut down. The second group consists of Marion and Sandusky Counties, where Whirlpool created new jobs.

Table 2 reveals significant increases in unemployment (18%) and decreases in manufacturing employment (35%) due to closures. The increase in unemployment comes from a base of between 1,000 and 2,000 people per treated county. This is non-negligible, considering that it does not account for workers that are retraining and those that have temporarily or permanently left the workforce. The decrease in manufacturing employment is sizable and confirms the importance of the Maytag plants to local county employment. Each of the counties with Maytag plants employed between 3,000 and 4,000 workers in manufacturing. So this translates to a decrease in the number of workers equivalent to the Maytag job cuts.

Column (5) shows no significant effect on local average wages in manufacturing. Columns (2) and (4) show that although the newly created Whirlpool jobs did not affect local unemployment, they led to a statistically significant increase in local manufacturing employment. The results in Column (6) suggest that this did not affect average local manufacturing wages.

The event study plots in Figure A.11 confirm timing alignment with Maytag employment changes, underscoring the local significance of appliance manufacturing jobs. They also show that the treatment effects were still present in 2008, the second year after treatment. The results suggest that appliance manufacturing jobs matter for local labor markets and

[22] To avoid adding noise from the Great Recession, I do not use data for 2009.

**Table 2:** Labor market effects of mass layoffs and new jobs

| | Unemployment | | Employment | | Wages | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Mass layoff | 0.184*** | | -0.348*** | | -0.008 | |
| | (0.058) | | (0.123) | | (0.048) | |
| New jobs | | 0.026 | | 0.087*** | | -0.004 |
| | | (0.033) | | (0.030) | | (0.019) |
| County fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,520 | 1,596 | 840 | 532 | 840 | 532 |

*Notes:* The dependent variable is the logarithm of county-level unemployment (Columns 1–2), manufacturing employment (Columns 3–4), and manufacturing wages (Columns 5–6). Observations are at the monthly level (Columns 1–2) or quarterly level (Columns 3–6). Standard errors (in brackets) are clustered at the county level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

can have persistent effects on employment and unemployment. This conclusion is further supported by Gathmann, Helm, and Schönberg (2020), who show that mass layoffs also lead to sizable and persistent negative spillover effects to the local economy, and Jacobson, LaLonde, and Sullivan (1993), who show that high-tenure workers suffer long-term earnings losses after separating from distressed firms.

# 4 Model

Three observations emerge from the preceding analysis. First, product portfolio decisions played a key role in shaping product market outcomes, making them central to evaluating the merger effects. Second, while firms adjusted their product offerings, no new firm entered the market, allowing me to abstract from firm-level entry. Third, labor market frictions and differences in production locations imply that who produces where matters for welfare.

These observations inform a model with manufacturers and consumers. Manufacturers choose product portfolios and prices; consumers choose among available products. The model unfolds in two stages. In the first stage, firms are endowed with a set of potential products and associated production locations. They observe product-specific fixed cost shocks, choose which products to offer, and hire workers. At this stage, they do not observe transitory demand or marginal cost shocks and form expectations over them. In the second stage, these shocks are realized and observed. Firms set prices for the chosen products. Consumers then observe all product characteristics and make discrete purchase decisions. I solve the game backward by searching for the subgame perfect Nash equilibria (SPNE) of the game.[23] To estimate the model parameters, I require the existence of a SPNE but not its uniqueness.

This framework captures the interaction between product market and labor market outcomes and provides a basis for evaluating the effects of different acquisitions.

## 4.1 Product portfolios

In the first stage, firms decide which products to offer and how to produce them. Each firm begins with a set of potential products $\mathcal{J}_{ft}$ it can supply in market $t$.[24] This set comprises products already sold by the firm at different retailers or markets, and new variants resulting from minor modifications to existing products. It excludes products requiring entirely new technological capabilities (e.g., introducing a firm's first front loader).[25]

Offering a product involves a fixed cost, including final development, marketing, and retailer-specific investments. Empirically, I consider annual markets. Given that sales of specific appliance models decline rapidly within one year of launch (Ashenfelter, Hosken, and Weinberg, 2013), I assume the fixed cost of offering a product in a given year is independent of previous product portfolios.

The fixed cost $F_{jt}$ of offering product $j$ comprises a brand-specific component $F_{b(j)}$ and a mean-zero product- and market-specific fixed-cost shock $\upsilon_{jt}$, such that $F_{jt} = F_{b(j)} + \upsilon_{jt}$, with $E[\upsilon_{jt}|j \in \mathcal{J}_{ft}] = 0$. Before portfolio selection, firms observe all product-specific fixed-cost shocks but not second-stage marginal cost and demand shocks, denoted $e_{jt} = (\xi_{jt}, \omega_{jt})$. Firms thus select their portfolios by balancing expected incremental variable profits for every product against the fixed costs of offering that product:

$$\max_{J_{ft} \subseteq \mathcal{J}_{ft}} \left\{ \pi_{ft} = E\left[VP(p)|J_{ft}\right] - \sum_{j \in J_{ft}} F_{jt} \right\} . \tag{3}$$

As portfolio selection is a discrete choice, optimality conditions hold only as inequalities.

## 4.2 Production and local labor demand

At the same time as firms choose their product portfolios, they also decide how to produce them. At this stage, firms form expectations about the second-stage shocks $e_{jt} = (\xi_{jt}, \omega_{jt})$,

[23] Whenever cost or demand shocks are observed by market participants, they remain unobserved by the econometrician.

[24] Since I have only temporal variation, I use "market" and "time" interchangeably.

[25] Because the data do not distinguish between new and continuing products, I cannot estimate separate fixed-cost bounds for each type.

which are not yet realized or observed.

Each potential product is associated with fixed product characteristics and a production location. Because manufacturers typically produce a given washer model for the U.S. market at a single plant, knowing a product's key characteristics allows me to identify its plant and thus its production country.

I model washer production using a Leontief technology:

$$q_{jt} = \min \left\{ \lambda_{1f(j)} K_{jt}, \lambda_{2c(j)} L_{jt}, \lambda_{3j} M_{jt} \right\} , \tag{4}$$

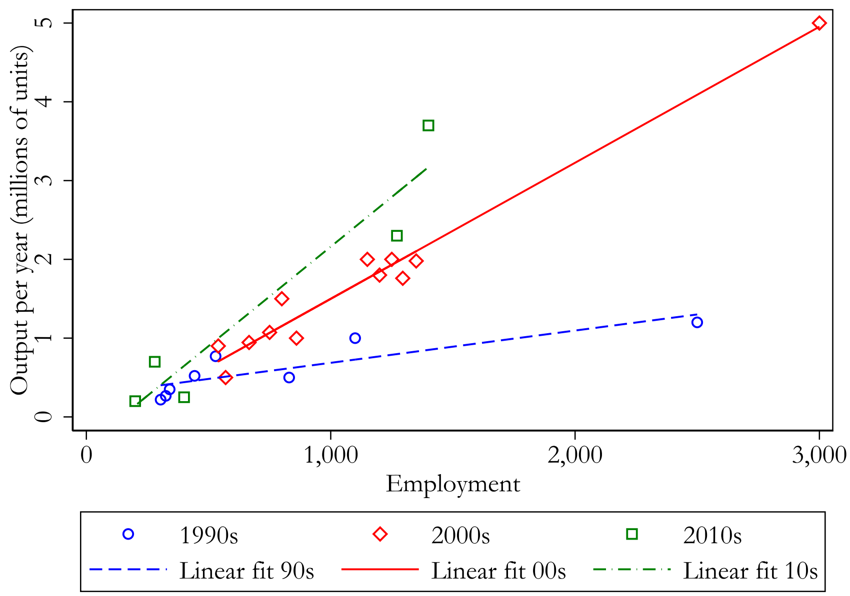
where $K_{jt}$, $L_{jt}$, and $M_{jt}$ are the amounts of capital, labor, and materials needed for producing quantity $q_{jt}$ of product $j$ at time $t$. The marginal products $\lambda_{1f(j)}$, $\lambda_{2c(j)}$, and $\lambda_{3j}$ correspond to capital, labor, and materials, respectively. Firms cannot substitute among inputs given these marginal products, but they may indirectly adjust marginal products through investments in technology or product selection. The marginal product of capital varies by firm ($f(j)$), labor by plant ($c(j)$) to capture scale economies, and material by product to accommodate differences between high- and low-end models.

Because employment effects of the merger are central to my analysis, the relationship between the number of workers and output is crucial. I assume each plant uses the same technology, differing only by size and potential economies of scale. Scale economies at the plant (rather than model) level seem appropriate, given that plants share many production processes across models and I observe employment and output data at the plant level. Table A.1 confirms that most models are produced at a single plant.

I specify two potential relationships between plant-level output and employment. Appendix III.A specifies an alternative Cobb-Douglas production function, $q_{c(j)t} = AL^{\zeta}_{c(j)t}$. I cannot reject $\zeta = 1$, indicating constant returns, but the fit to data is poor. Instead, Figure 4 plots annual plant-level output and employment for plants where this data is available. After splitting the sample according to the decade of the observation, the plot shows an approximately linear plant-level relationship between employment and output. This indicates that washer plants require a certain number of manufacturing workers to operate, after which output increases linearly in the number of workers. Although marginal costs appear to be constant, variable costs decrease with scale.

Furthermore, the slope of this relationship becomes steeper over time. This suggests that the marginal product of labor increases over time, most likely due to technological improvements. Overall, the data suggests that the marginal product of labor is constant between plants at a given point in time but increases over time. An important caveat here is that there is only limited data available on plant-level output and employment.

**Figure 4:** Plant-level output and employment




*Notes:* The figure shows the relationship between plant-level output and employment.

To formalize this, I specify the relationship as:

$$q_{c(j)t} = \begin{cases} 0 & \text{if } L_{c(j)t} < \psi_0, \\ \psi_1 \cdot (L_{c(j)t} - \psi_0) & \text{if } L_{c(j)t} \geq \psi_0, \end{cases} \tag{5}$$

where $\psi_0$ is the overhead labor requirement for operating a plant without output, and $\psi_1$ is the annual marginal product of labor. Estimating the inverse specification,

$$L_{c(j)t} = \psi_0 + \psi_1^{-1} q_{c(j)t} + \rho_{c(j)t} \,, \tag{6}$$

where $\rho_{c(j)t}$ captures measurement error in plant-level employment, yields the parameters in Table 3. Using the full sample, the overhead labor requirement $\psi_0$ is 315 workers, dropping to 161 workers for observations from the 2000s. The estimated annual marginal product of labor, $\psi_1$, is 2096 washers per worker for the full sample and 1780 washers per worker for the restricted sample, with a 95% confidence interval between 1585 and 2029.

Marginal costs are additive due to the Leontief production technology. Including transportation, product-level marginal cost is:

$$mc_{jt} = \lambda_{1f(j)}^{-1} r_{f(j)t} + \psi_1^{-1} w_{c(j)t} + \lambda_{3j}^{-1} m_t + \tau_t d_{c(j)t} + \omega_{jt} \,, \tag{7}$$

**Table 3:** Relationship between annual plant-level employment and output

| | (1) | (2) |
|---|---|---|
| $\psi_0$ | 315.1516** | 161.3267** |
| | [57.7550,572.5482] | [20.9060,301.7474] |
| $\psi_1^{-1}$ | 0.0005*** | 0.0006*** |
| | [0.0003,0.0006] | [0.0005,0.0006] |
| Restrict to 2000s | No | Yes |
| Observations | 25 | 12 |

*Notes:* The dependent variable is total plant-level employment. Column (2) includes observations from 2000–2009 only. 95% confidence intervals are shown in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

where $r_{f(j)t}$, $w_{c(j)t}$, and $m_t$ are input prices for capital, labor, and materials; $d_{c(j)t}$ is the distance between the production location of product $j$ and the destination market; $\tau_t$ is transportation cost per washer for every distance unit; and $\omega_{jt}$ is a product-level marginal cost shock realized after input and portfolio choices. This can be thought of as an unanticipated shock to per-unit material costs.

Firms take input prices as given. Local labor market effects can arise even with competitive input markets. Suppose local labor markets have convex supply and worker mobility frictions, combined with fixed costs of operating a plant and sunk relocation costs. In this case, plant openings or closures shift local labor demand. Adjustments occur primarily via employment on the elastic portion of labor supply or via wages on the inelastic portion. While fully modeling local labor markets and estimating labor market power would allow more flexibility on the employment side, this is beyond the scope of this paper. Because Table 2 shows employment adjusted without wage changes following plant openings and closures, I assume labor markets operate on the elastic portion. Hence, I keep wages fixed and allow employment to adjust.

Even with efficient local labor markets, policymakers may choose to invest public funds to shift local labor demand (e.g., by offering tax incentives), provided the investment cost is lower than the resulting surplus. If manufacturers have wage-setting power, a merger-induced decrease in local labor demand could lower local wages, partially offsetting the employment loss (Kroft et al., 2025). However, since wages did not adjust in the descriptive analysis, this concern appears limited in this application.

Domestic labor demand for firm $f$ can thus be expressed as:

$$LD_{ft} = \psi_0 \times (\#\text{domestic plants}_{ft}) + \sum_{j \in J_{ft}} \psi_1^{-1} E[q_{jt}] \times \text{domestic share}_{jt}, \tag{8}$$

where domestic share$_{jt}$ is the fraction of product $j$ produced domestically.[26] Firms choose employment based on expected equilibrium product market quantities, which depend indirectly on wages via marginal costs.

### 4.3 Pricing and product demand

In the second stage, firms observe demand and marginal cost shocks, then set prices. Each firm $f$ chooses prices for its offered products, $J_{ft}$, to maximize variable profits:

$$VP_{ft} = \sum_{j \in J_{ft}} (p_{jt} - mc_{jt}) s_{jt} S_t \, , \tag{9}$$

where $p_{jt}$ and $mc_{jt}$ are price and marginal cost of product $j$ at time $t$, $s_{jt}$ is its market share, and $S_t$ is total market size. Equilibrium prices satisfy the first-order conditions:

$$p_{jt} = mc_{jt} - [(\nabla_p s \bullet \Lambda)^{-1} s]_{jt} \, , \tag{10}$$

where $\Lambda$ is the ownership matrix capturing firm-level product ownership, and $\nabla_p s$ is the matrix of market-share derivatives with respect to prices.

Household demand for washers follows a discrete-choice framework as in Berry, Levinsohn, and Pakes (1995) and Berry, Levinsohn, and Pakes (2004). In each year, households either buy one washing machine from the available set $J_t$ or choose an outside good (keeping their existing washer or having none).

Household $i$'s utility from washer $j$ in year $t$ is:

$$u_{ijt} = x_{jt}\beta + \sigma^{FL}\nu_{it}^{FL}x_{jt}^{FL} - exp(\alpha + \kappa_\alpha \iota_{it})p_{jt} + \xi_{jt} + \epsilon_{ijt} \, . \tag{11}$$

The vector $x_{jt}$ includes non-price product characteristics (e.g., front loader indicator, brand repair rate, number of programs), brand and retailer dummies, year fixed effects, and brand-specific trends.[27] The price of washer $j$ is $p_{jt}$.

[26] While most products are produced in a single plant, some transitional cases involve multiple plants. See Appendix Table A.1.

[27] Specifically, product characteristics include: brand repair rate, advertising expenditures, front loader, Korean front loader, Fisher & Paykel front loader, high-end European front loader (Asko, Bosch, Miele), agitator, stacked pair, stainless steel exterior, white exterior, Energy Star certification, extra noise insulation,

The average taste for non-price characteristics is captured by $\beta$. Households differ in income $\iota_{it}$ and in their idiosyncratic preference for front loaders $\nu_{it}^{FL} \sim \mathcal{N}(0,1)$, scaled by $\sigma^{FL}$. Price sensitivity varies exponentially with household income through parameters $\alpha$ and $\kappa_\alpha$, ensuring negative marginal utility of price.[28]

The remaining utility components include a product-level unobservable common to all households, $\xi_{jt}$, capturing unmeasured product quality and transitory demand shocks, and an idiosyncratic household-product shock, $\epsilon_{ijt}$, drawn from a type-I extreme-value (Gumbel) distribution.

To simplify notation, I decompose utility into mean utility $\delta_{jt}$ (constant across households) and household-specific deviations $\mu_{ijt} + \epsilon_{ijt}$. Parameters of the demand model are collected in $\theta = (\theta_1, \theta_2)$, with linear parameters $\theta_1 = (\beta)$ and nonlinear parameters $\theta_2 = (\sigma^{FL}, \alpha, \kappa_\alpha)$. The utility of the outside good is normalized to zero.

Given these distributional assumptions, market shares follow a familiar logit form. Integrating over the joint distribution of household demographics $P_D(D)$ and taste shocks $P_\nu(\nu)$ yields predicted market shares:

$$s_{jt} = \int \frac{exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k \in J_t} exp(\delta_{kt} + \mu_{ikt})} P_D(D) P_\nu(\nu)\,. \tag{12}$$

## 4.4 Connection between hiring and product market decisions

At first glance, product market and hiring decisions might seem only loosely connected. However, by explicitly modeling the link between output and employment and incorporating local production costs into product-level marginal costs, the model can capture how shifts in local production costs affect manufacturers' labor demand.

For example, in 2005, Whirlpool produced most front loaders for the U.S. market in Germany, whereas Maytag produced them domestically. Both firms produced all top loaders domestically. Between 2005 and 2007, the German real exchange rate relative to the U.S. increased. Simultaneously, Whirlpool opened a front loader plant in Mexico post-merger while maintaining domestic top-loader production. Consequently, front loaders from Germany became relatively less attractive, and those relocated to Mexico more attractive. By 2009, Whirlpool had moved all front loader production for the U.S. market to Mexico. It then shifted it entirely back to the U.S. by 2013.

child lockout, plus retailer, brand, and year fixed effects, and linear brand-specific trends.

[28] Household income is top-coded at $400,000. Although households with incomes above $400,000 are present in the household samples drawn from the CPS, TraQline groups all respondent households with an income above $250,000 together. In practice, setting a higher cap has negligible effects on estimated parameters.

As local production costs for front loaders produced in Germany increased, but local production costs for front loaders relocated to Mexico fell, the share of German-made Whirlpool washers declined. The share of front loaders among Whirlpool's post-merger sales rose from 24 percent in 2005 to 27 percent in 2007. When front loader production fully moved to Mexico, reaching its lowest relative cost compared to top-loaders, this share peaked at 29 percent. By 2013, after relocating front loader production entirely to the U.S., and hence increasing their relative production costs, front loaders accounted for only 19 percent of Whirlpool's sales. Because labor demand is proportional to output, it increases when local production costs fall, and vice versa.

This is exactly what the model predicts. Given production locations, if production costs rise for some products but not others, firms reduce offerings of affected products and raise their prices, diverting sales toward products without a cost increase. This results in lower output and employment at plants facing higher local costs.

# 5 Estimation

This section describes the estimation of the model parameters, starting with demand, as later estimates build on these.

## 5.1 Demand

The demand estimation closely follows Berry, Levinsohn, and Pakes (2004). Full details on the moments and procedure are provided in Appendix IV.B; here I summarize how the data variation identifies the parameters.

As defined earlier, I partition the demand parameters $\theta$ into linear parameters $\theta_1$ and nonlinear parameters $\theta_2 = (\sigma^{\text{FL}}, \alpha, \kappa_\alpha)$. I estimate $\theta_2$ using the method of simulated moments (MSM) with three moment conditions. The first two moments match simulated household-level moments to their empirical counterparts, and the third exploits the orthogonality condition from excluding the real exchange rate cost shifter from utility. With three moments and three nonlinear parameters, the system is exactly identified. Conditional on $\hat{\theta}_2$, the linear parameters $\theta_1$ are estimated by ordinary least squares (OLS).

The first micro-moment matches the correlation between purchasing a front loader and the share of front loaders among second-choice brand for each household.[29] Although *TraQline* only records second-choice brands (not specific models), the front loader share differs

[29] See Equation 22 in Appendix IV.B.

considerably across brands. The correlation of 0.4 indicates unobserved taste heterogeneity for front loaders, influencing substitution patterns.

The second micro-moment matches the correlation between household income and washer purchase prices, which is 0.5.[30] This suggests lower price sensitivity among higher-income households.

To address price endogeneity due to correlation with the unobserved demand shock $\xi_{jt}$, I instrument using the product-level real exchange rate described in Section 2. The RER captures product-level marginal cost variation from local wages and exchange rates at each production location but is orthogonal to U.S. product-level demand shocks, thus satisfying exogeneity. Both prices and the RER are deflated to 2012 dollars. For the specification with homogeneous price sensitivity, the RER is a conventional instrument; with heterogeneous price sensitivity, the nonlinear identification relies on the moment condition $E[RER_{c(j)t}\xi_{jt}] = 0$, preserving the exclusion restriction.

To estimate linear utility parameters $\beta$, I first recover mean utilities $\delta$ by matching simulated to observed market shares. For identification, I impose:

**Assumption 1.** $E[e_{jt}|X_{jt}, F_{jt}] = 0$ *for each* $j \in \mathcal{J}_t$.

Thus, second-stage demand and marginal cost shocks are independent of nonprice characteristics and fixed costs of offering a product. Following Eizenberg (2014), this assumption is slightly stronger than assuming $e_{jt}$ is realized after product choices, as firms cannot predict these unobservable, transitory shocks. Nonetheless, firms may still predict demand and costs related to observables, which are controlled for explicitly.

An essential input for the demand estimation is market size, defined as the fraction of the population considering a washer purchase. *TraQline* provides total respondent counts, including non-buyers. Given washers' roughly ten-year lifespan and the fact that households may start considering purchasing a new washer in the years prior to the end of a washer's lifespan, I assume every seventh household considers buying a washer annually, making market size one-seventh of the surveyed households each year.

Standard errors for all demand parameters are clustered at the brand level using a residual bootstrap.

## 5.2 Marginal costs and production

I compute marginal costs by inverting each firm's first-order conditions for profit maximization. Under the stated assumptions, each product has a unique marginal cost and markup

[30] This corresponds to Equation 21 in Appendix IV.B. See also Figure A.12 for a scatter plot of the relationship between household income and price.

that rationalizes the data.

The decomposition of marginal costs follows directly from Equation (7). I estimate:

$$mc_{jt} = FE_f + \gamma_1 RER_{c(j)t} + \gamma_2 d_{c(j)t} + \gamma_3 x_j + \omega_{jt}\,. \tag{13}$$

Firm fixed effects $FE_f$ capture differences in capital intensity across firms. The real exchange rate $RER_{c(j)t}$ is a product-level cost shifter capturing local wage and nominal exchange rate fluctuations. Given constant returns to scale, marginal costs scale linearly with wages, implying $\gamma_1$ absorbs the labor productivity parameter $\psi_1^{-1}$ from Equation (7). Distance $d_{c(j)t}$ measures distance from each plant to the market center. The vector of nonprice characteristics $x_j$ captures material cost differences across products, while $\omega_{jt}$ denotes transitory material cost shocks. Finally, the estimated residual $\widehat{\omega}_{jt}$ is computed as the difference between observed and predicted marginal costs.

## 5.3 Fixed cost bounds

The product assortment model in Section 4.1 yields inequality conditions, precluding point identification of fixed costs. Instead, I use partial identification to estimate bounds on these fixed costs for each brand.

To obtain fixed-cost bounds, I first define each firm's set of potential products. This includes all products the firm could have offered (*potential products*, denoted $\mathcal{J}_{ft}$), distinguishing between those actually offered (*active products*, denoted $J_{ft}$) and those not offered (*inactive products*, denoted $\tilde{J}_{ft}$).

The set of potential products includes all products a firm is technologically capable of producing. The active products are observed in the data. I identify inactive products as variations of active products that the firm did not offer. For any active product (e.g., a front loader by KitchenAid sold at Sears), all versions of the product that I do not observe in the data (e.g., a front loader by KitchenAid sold at another retailer) is an inactive product. Thus, if a firm does not offer any front loaders, I do not assume it could have introduced one in that year. The fixed costs thus reflect marketing expenditures, retailer-specific investments, and product customization, but exclude costs of developing entirely new technologies.

I follow the procedure in Eizenberg (2014) closely to estimate these bounds. Under the assumption that observed product entry corresponds to a pure-strategy subgame-perfect Nash equilibrium, no firm can unilaterally deviate profitably. In practice, I estimate fixed-cost bounds using conditions derived from the absence of profitable one-step deviations.[31]

[31] Additional restrictions could come from multi-step deviations. However, idiosyncratic fixed-cost shocks $\upsilon_{jt}$ for different products make these difficult to incorporate.

I denote the equilibrium product portfolio (i.e., the set of active products) of firm $f$ at time $t$ as $J^*_{ft}$. For each active product $j$, the fixed cost is bounded above by the expected incremental profit from offering that product, holding other products fixed:

$$F_{jt} \leq E[VP_{ft}(J^*_{ft}) - VP_{ft}(J^*_{ft} - \mathbf{1}^j_{ft})] \equiv \bar{F}_{jt}\,, \tag{14}$$

where $\bar{F}_{jt}$ is the upper bound on the fixed costs of offering product $j$ at time $t$.

Similarly, for each inactive product, the fixed cost is bounded below by the expected incremental variable profit if the product were added, again holding other products fixed:

$$F_{jt} \geq E[VP_{ft}(J^*_{ft} + \mathbf{1}^j_{ft}) - VP_{ft}(J^*_{ft})] \equiv \underline{F}_{jt}\,, \tag{15}$$

where $\underline{F}_{jt}$ is the lower bound on the fixed costs of offering product $j$ at time $t$.

Directly estimating the upper bound using active products and the lower bound using inactive products would be inadmissible since product portfolio decisions depend on $\upsilon_{jt}$. However, the product-specific fixed cost shocks have mean zero conditional on the product being part of the set of potential products. With estimates of the lower bound of fixed costs of offering active products and estimates of the upper bound of fixed costs of offering inactive products, I can thus construct unbiased bounds on brand-level average fixed costs $F_{b(j)}$.

**Assumption 2.** $\sup_{j\in\mathcal{J}_{bt}} F_{jt} = F^U_{b(j)t} < \infty$ *and* $\inf_{j\in\mathcal{J}_{bt}} F_{jt} = F^L_{b(j)t} > -\infty$ *(bounded support)*

Assumption 2 requires bounded support for fixed costs. While unlimited costs may be plausible for breakthrough technologies, here fixed costs reflect the costs of offering a product at another retailer or incremental product adjustments within existing technological capabilities. Thus, an upper bound seems plausible. Since costs of product introduction are always nonnegative, a finite lower bound $F^L_{b(j)t}$ is also natural.

**Assumption 3.** $[F^L_{b(j)}, F^U_{b(j)}] \subseteq \mathrm{supp}($*expected incremental profit from adding or removing any single product of brand* $b)$

Assumption 3 further restricts the fixed-cost support. Specifically, the fixed-cost distribution for potential products of brand $b$ must lie within the range of expected incremental variable profits from adding or removing any single brand-$b$ product. The intuition is straightforward: If a brand includes a blockbuster product so profitable that it is always offered, then this product is always part of the set of active products. Thus, the incremental variable profit of the most profitable product among the active products sets an upper bound on all fixed costs. Similarly, if there exists a potential product that is so unprofitable such that it is never offered, then its incremental variable profit sets a lower bound for fixed costs.

I fill in the missing lower bounds for active products using the minimum expected incremental variable profit among inactive products of the same brand. Conversely, missing upper bounds for inactive products are assigned using the maximum incremental variable profit among active products of that brand. Thus, product-level bounds on fixed costs for active and inactive products become:

$$L_{jt}(\theta) = \begin{cases} V^L_{b(j)t}(\theta) & j \in J_{bt} \\ \underline{F}_{jt}(\theta) & j \in \tilde{J}_{bt} \end{cases} \qquad U_{jt}(\theta) = \begin{cases} \bar{F}_{jt}(\theta) & j \in J_{bt} \\ V^U_{b(j)t}(\theta) & j \in \tilde{J}_{bt} \end{cases}.$$

Since $E[\upsilon_{jt}|j \in \mathcal{J}_{ft}] = 0$, and with the estimates of the upper and lower bounds on fixed costs for all $j \in \mathcal{J}_{ft}$, applying unconditional expectations yields unbiased bounds on brand-level fixed costs:

$$E[L_{jt}(\theta)] \leq F_{b(j)t} \leq E[U_{jt}(\theta)] \quad \forall j \in \mathcal{J}_{bt}\,. \tag{16}$$

Next, I estimate the components of Equation (16). In Section 7, I analyze how the merger affects the incentives of brand owners to adjust their product portfolios using product portfolios in 2005 (pre-merger) and 2007 (post-merger). I therefore use the same two years' data to estimate fixed-cost bounds.

For inactive products, I replace the population parameter $\theta$ with its estimator $\hat{\theta}$, yielding $L_{jt}(\hat{\theta}) = \underline{F}_{jt}(\hat{\theta})$ for $j \in \tilde{J}_{bt}$. Similarly, for active products, $U_{jt}(\hat{\theta}) = \bar{F}_{jt}(\hat{\theta})$ for $j \in J_{bt}$. Expectations are approximated using the sample mean across 500 draws from the joint empirical distribution of the demand and marginal cost shocks, $e_{jt}$. Then, I use $\min_{j \in \tilde{J}_{bt}}\{\underline{F}_{jt}(\hat{\theta})\}$ as an estimator for $V^L_{b(j)t}(\theta)$ and $\max_{j \in J_{bt}}\{\bar{F}_{jt}(\hat{\theta})\}$ as an estimator for $V^U_{b(j)t}(\theta)$.

The resulting estimated interval for each brand is given by:

$$\left[\bar{l}^b_n(\hat{\theta}),\, \bar{u}^b_n(\hat{\theta})\right], \quad \text{where} \quad \bar{l}^b_n(\hat{\theta}) = \frac{1}{n^b}\sum_{j=1}^{n^b} L_j(\hat{\theta}), \quad \bar{u}^b_n(\hat{\theta}) = \frac{1}{n^b}\sum_{j=1}^{n^b} U_j(\hat{\theta}), \tag{17}$$

and $n^b$ is the number of potential products for brand $b$. This procedure yields unbiased and conservative fixed-cost bounds.

Finally, I construct $(1-\alpha) \times 100\%$ confidence intervals for $F_b$ following Imbens and Manski (2004) and Eizenberg (2014). These intervals are based on one-sided bounds around the point estimates:

$$\left[\bar{l}^b_n(\hat{\theta}) - \frac{S_l(\hat{\theta})}{\sqrt{n^b}} z_{1-\alpha}, \quad \bar{u}^b_n(\hat{\theta}) + \frac{S_u(\hat{\theta})}{\sqrt{n^b}} z_{1-\alpha}\right], \tag{18}$$

where $S_l(\hat{\theta})$ and $S_u(\hat{\theta})$ are standard deviation estimators for $L_j$ and $U_j$. I obtain these estimates using 200 bootstrap samples, which also account for variability in demand parameter estimates and variable profit simulations.

# 6 Parameter Estimates

## 6.1 Demand

Table 4 presents the demand estimates. Column (1) reports the first-stage regression, relating washer prices to the real exchange rate instrument, controlling for all covariates and fixed effects. A one-unit increase in RER raises prices by \$203. The Kleibergen–Paap F-statistic of 31 indicates a strong instrument.

The remaining columns use the estimated mean utility of purchasing product $j$ at time $t$, $\delta_{jt}$, as the dependent variable. Columns (2) and (3) report estimates from the simple logit model, first by OLS, then by IV. Accounting for price endogeneity decreases the average own-price elasticity from $-0.96$ (OLS) to $-2.06$ (IV). Column (4) shows the nonlinear parameters from the full mixed-logit model. These estimates highlight significant household-level heterogeneity in preferences. Higher-income households exhibit lower price sensitivity. Moreover, households purchasing front-loaders have systematically higher unobserved preferences for front-loaders. Incorporating these heterogeneities, the average own-price elasticity further decreases to $-2.54$.

## 6.2 Marginal cost and production

Figure 5 displays the distribution of estimated marginal costs across all products.

Figure 6 plots marginal costs and Lerner indices by brand owner over time. Although marginal costs decline around the merger, this decrease occurs industry-wide, affecting both merging parties and rival firms. Hence, these cost reductions are not merger-specific, and any counterfactual analyses must reflect this broader trend. The observed cost pattern aligns with the decline in European washer prices documented in Section 3 and is consistent with general industry-wide savings through production relocation and technological advances. Concurrently, markups—as captured by Lerner indices—increase.[32]

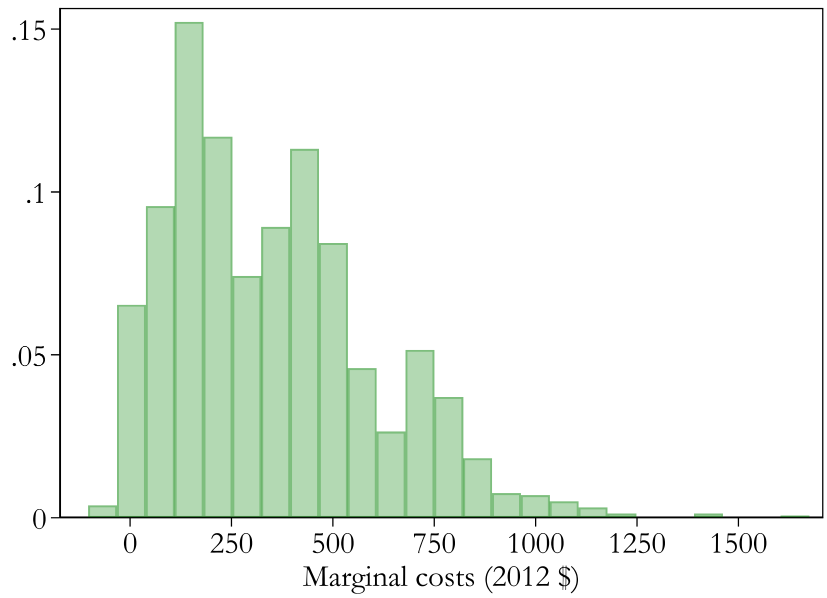
[32]The pronounced fluctuation in Samsung's Lerner index between 2006 and 2007 should be interpreted

**Table 4:** Demand estimates

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | First stage | Logit OLS | Logit IV | Mixed logit |
| *Dependent variable:* | Price | $\hat{\delta}_{jt}$ | $\hat{\delta}_{jt}$ | |
| *Linear parameters* | | | | |
| Real exchange rate | 2.033$^{***}$ | | | |
| | (0.365) | | | |
| Price ('00 2012 $) | | -0.164$^{**}$ | -0.351$^{**}$ | |
| | | (0.062) | (0.178) | |
| *Nonlinear parameters* | | | | |
| Common price coefficient $\alpha$ | | | | -0.676$^{***}$ |
| | | | | (0.033) |
| Income effect $\kappa_\alpha$ | | | | -0.209$^{***}$ |
| | | | | (0.024) |
| Unobserved taste $\sigma^{FL}$ | | | | 2.493$^{***}$ |
| | | | | (0.068) |
| Characteristics | *Yes* | *Yes* | *Yes* | *Yes* |
| Retailer FE | *Yes* | *Yes* | *Yes* | *Yes* |
| Brand FE | *Yes* | *Yes* | *Yes* | *Yes* |
| Brand time trends | *Yes* | *Yes* | *Yes* | *Yes* |
| Year FE | *Yes* | *Yes* | *Yes* | *Yes* |
| Observations | 1,590 | 1,586 | 1,590 | 1,590 |
| Kleibergen–Paap F-statistic | 31.041 | | | |
| Avg. own-price elasticity | | -0.964 | -2.058 | -2.542 |

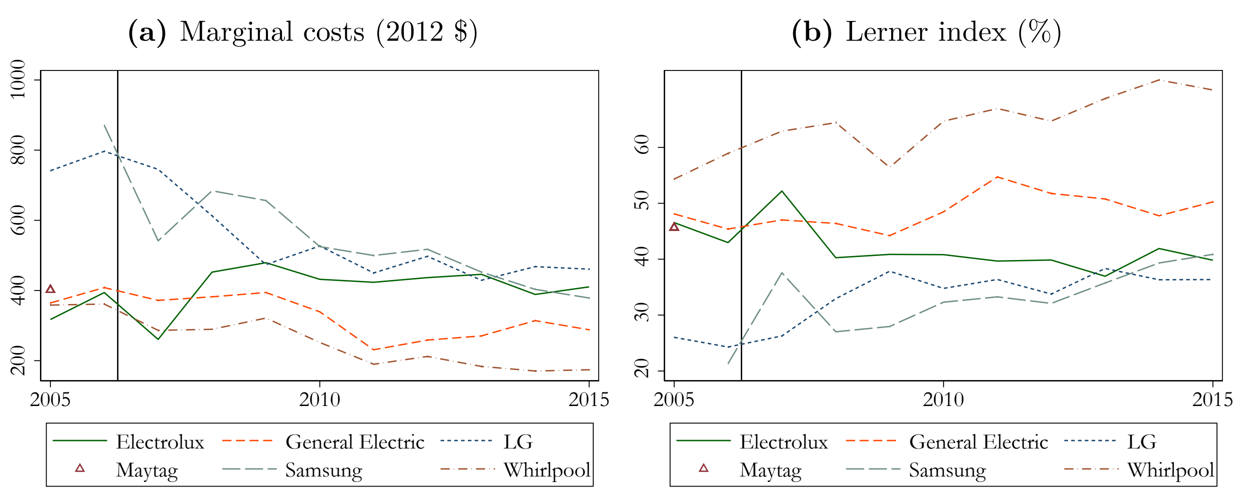
*Notes:* Column (1) reports the first-stage regression results of prices on the real exchange rate. Column (2) presents estimates from the simple logit model without instrumentation. Column (3) shows estimates from the simple logit using the RER as an instrument for price. Column (4) displays results from the mixed logit model described in Section 4. Standard errors are clustered at the brand level. Own-price elasticities of residual demand are computed at the product level and averaged across products, weighting by sales volume. Estimates for nonprice characteristics are presented in Table A.4. Significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Figure 5:** Histogram of product-level marginal cost estimates




*Notes:* Histogram of estimated marginal costs (deflated to 2012 dollars) across all products in the sample.

**Figure 6:** Evolution of marginal cost and Lerner index by brand owner




*Notes:* Marginal costs (left panel) and Lerner index (right panel) by brand owner over time. The vertical line indicates Whirlpool's Maytag acquisition. Whirlpool includes Maytag products from 2006 onward.

**Table 5:** Marginal cost decomposition

| | **Marginal costs (2012 $)** |
|---|---|
| Real Exchange Rate | 186.087*** |
| | (36.280) |
| Distance ('000 km) | 8.544 |
| | (8.275) |
| Front Loader | 16.489 |
| | (20.051) |
| Agitator | -244.454*** |
| | (26.785) |
| Characteristics | *Yes* |
| Retailer FE | *Yes* |
| Brand FE | *Yes* |
| Brand time trends | *Yes* |
| Year FE | *Yes* |
| N | 1,586 |

*Notes:* The table presents regression results of product-level marginal costs on proxies for labor and shipping costs, product characteristics, fixed effects, and brand-specific time trends.

Table 5 quantifies how marginal costs depend on labor costs (captured by the deflated RER), shipping distance, product characteristics, and firm-specific fixed effects.

Although the estimate for distance-related transportation costs is noisy, the point estimate aligns closely with external reports. Specifically, shipping washers from Germany to the U.S. increases costs by approximately $59 (in 2012 dollars), matching Whirlpool's reported cost in 2005.[33]

The deflated RER captures cross-country wage differences. For 2006, the RER was 0.28 for China, 0.64 for Mexico, and 1 for the U.S. (since it is normalized by U.S. prices).[34] Consequently, moving production from the U.S. to Mexico reduces labor costs by $67 per washer, while shifting to China reduces them by $134. However, relocating production to China raises transportation costs by $81. Thus, the total marginal cost impact of moving production from the U.S. to China or Mexico in 2006 would have been roughly equivalent.

cautiously, due to the small number of Samsung products available at that time.

[33]Whirlpool reports that shipping front-loaders from its plant in Germany to the U.S. cost $50 in 2005 ($57 in 2012 dollars). See https://www.nytimes.com/2005/06/17/business/worldbusiness/globalization-its-not-just-wages.html.

[34]Within-country plant-level wage differences are arguably second-order compared to cross-country differences.

**Table 6:** Brand-level fixed costs of adding a product ($M)

| **Brand owner** | **Brand** | **95% confidence sets** | $\mathbf{n^b}$ |
|---|---|---|---|
| Maytag | Admiral | $[6.3, 12.6]$ | 10 |
| | Amana | $[1.7, 5.1]$ | 15 |
| | Maytag | $[5.3, 25.3]$ | 30 |
| Whirlpool | KitchenAid | $[0.9, 3.4]$ | 10 |
| | Roper | $[1.7, 11.2]$ | 20 |
| | Whirlpool | $[14.6, 30.9]$ | 30 |
| General Electric | General Electric | $[2.5, 18.4]$ | 30 |
| | Hotpoint | $[0.7, 2.4]$ | 15 |
| Electrolux | Frigidaire | $[2.7, 11.8]$ | 20 |
| | Westinghouse | $[0.6, 2.1]$ | 20 |
| LG | LG | $[5.1, 16.4]$ | 20 |
| Samsung | Samsung | $[1.0, 6.5]$ | 10 |

*Notes:* Brand-level fixed cost bounds are estimated from all active and potential products in 2005 and 2007.

### 6.3 Fixed cost bounds

Finally, Table 6 reports the estimated brand-level fixed cost bounds for offering a product. Recall that a product is defined as a combination of brand, retailer, and major washer characteristics. Hence, the estimated fixed cost intervals represent the costs associated with offering a specific product category (brand–characteristic combination) at a given retailer.

The 95 percent confidence sets indicate that fixed costs tend to be larger for brands with higher market shares, such as Maytag and Whirlpool, compared to brands with lower market shares, such as KitchenAid, Hotpoint, and Westinghouse. This pattern could reflect that brands with larger market share require retailers to stock comprehensive product assortments, demanding greater floor space and higher marketing expenditures.

## 7 Welfare Effects of the Whirlpool Acquisition

With the estimated demand and supply parameters, I compare the welfare effects of alternative acquisitions of Maytag. First, I contrast the Whirlpool acquisition with a scenario in which Maytag remains independent, explicitly modeling endogenous product portfolios and employment outcomes. Although maintaining a standalone Maytag was not feasible, this scenario provides a useful intermediate step for the comparison between acquirers.

Second, I compare Whirlpool's acquisition of Maytag to the hypothetical acquisition by Haier. The richest comparison incorporates how production relocations affect marginal costs, prices, consumer welfare, and employment.

## 7.1 Portfolio choice algorithm

Before presenting the welfare comparisons, I briefly discuss how firms endogenously choose product portfolios. Producers with market shares above 3 percent in any year can adjust portfolios (Electrolux, General Electric, LG, Maytag, Samsung, and Whirlpool).[35] This leaves 135 potential products, alongside 69 products offered exogenously.

A known complexity in product portfolio choice games is equilibrium multiplicity. One way to identify the set of potential equilibria is to estimate the expected variable profits for all possible product entry combinations and then check whether there are any combinations of product entry costs contained in the fixed cost confidence sets that make these product portfolios an SPNE of the entry game.[36] In my case, this is computationally infeasible since there are $2^{135}$ candidate equilibria. Instead, following Fan and Yang (2020), I construct a heuristic portfolio optimization algorithm leveraging the observed pre-merger equilibrium as a starting point. This choice assumes that post-merger equilibria closer to pre-merger portfolios are more likely.

Specifically, firms iteratively optimize product portfolios by checking for profitable one-step deviations—either adding an inactive product or removing an active one—until no further profitable deviations exist. To reduce computational complexity, the algorithm optimizes portfolios at the brand rather than firm level. Because fixed costs are only set-identified, I repeat this process for 50 fixed-cost draws and report 95-percent confidence sets for welfare outcomes.[37]

## 7.2 The Whirlpool acquisition of Maytag

I first compare the Whirlpool acquisition to a scenario in which Maytag continues as a standalone firm, abstracting initially from production relocations. This intermediate step also corresponds to comparing acquisitions by Whirlpool and Haier in the product market if marginal costs remain unchanged, as Haier had no pre-merger U.S. presence.

The simulations rely on estimated demand and supply parameters from 2005–2015, assuming time-invariant preferences for characteristics. Brand-specific time trends and year fixed effects allow for time-varying preferences for brands and differences in outside options and input costs, respectively.

In scenarios without portfolio adjustments I hold firms' 2005 product portfolios fixed,

[35] Smaller competitors' portfolios, and products sold at retailers other than the major five, remain fixed.

[36] This is the approach taken by Eizenberg (2014) in a setting where there are four brands and four product types. After adding some additional restrictions, he ends up with $2^9 = 512$ candidate equilibria.

[37] Further technical details are in Appendix VI.A. Appendix Tables A.8 and A.9 present results for alternative fixed-cost draws.

setting brand trends, deflated RER, and year fixed effects to 2005 levels. In scenarios with endogenous portfolios, I fix market conditions at their 2007 values, using all potential products from both 2005 and 2007.[38] Since I observe the acquisition scenario associated with the greatest increase in market power, I observe conditions under which rivals like LG or Samsung had the strongest incentive to expand their product offerings, since less intensive competition encourages rival product entry. Thus, any product not offered by rivals post-merger would also likely have remained inactive absent the merger.

Table 7 shows that without portfolio adjustments, a Whirlpool acquisition raises average prices by 3.2 percent, increases Maytag and Whirlpool prices by 6.9 and 5.9 percent, respectively, and reduces consumer welfare by $167 million annually. Without relocations, the merger costs 127 domestic jobs due to reduced output and substitution toward imports. Including observed relocations post-merger, the Whirlpool acquisition reduces employment by 735 jobs, reflecting both variable labor (286 jobs shifting to Mexico) and fixed overhead employment (322 jobs from closing two Maytag plants).

When firms adjust product portfolios endogenously, the merged entity reduces its product offerings to avoid cannibalization. However, the merger does not substantially alter rivals' incentives to expand product lines relative to the standalone scenario.

Contrary to the Department of Justice's assessment, endogenous portfolio adjustments exacerbate consumer harm, as fewer products remain available without significant portfolio expansions from rivals. These findings align with those of Fan and Yang (2020) and Fan and Yang (2025), contrasting with Wollmann (2018).

Notably, endogenous product choices also significantly amplify domestic employment losses, increasing them by 37 percent compared to fixed portfolios. Thus, considering portfolio decisions is crucial for accurately assessing employment impacts, even if policymakers focus primarily on labor outcomes.

### 7.3 Whirlpool vs. Haier as acquirers for Maytag

Next, I compare Maytag's acquisition by Whirlpool versus Haier. Given Haier's minimal pre-merger presence in the U.S. market, absent marginal cost changes, a Haier acquisition is equivalent for consumers to Maytag remaining standalone. Employment effects, however, differ substantially due to distinct production relocation strategies. I assume Haier would offshore all production to China, whereas Whirlpool's observed post-merger plan offshored front-loader production to Mexico and maintained top-loader production domestically.

Table 8 shows the differences between these two scenarios. Without marginal cost

[38] If product versions differ across years, I use the 2007 version.

**Table 7:** Simulation of a Maytag acquisition by Whirlpool

| *Product portfolios:* | Pre-acquisition | Endogenous |
|---|---|---|
| *Number of products* | | |
| Maytag | – | -1.5 |
| | – | [-3.5, 0.5] |
| Whirlpool | – | -1.6 |
| | – | [-3.3, 0.2] |
| LG + Samsung | – | 0.4 |
| | – | [-0.9, 1.8] |
| Electrolux + GE | – | 1.3 |
| | – | [-0.7, 3.3] |
| Overall industry | – | -1.3 |
| | – | [-4.2, 1.6] |
| *Prices and consumer welfare* | | |
| Average price | 3.2% | 4.1% |
| | [1.9%, 4.6%] | [3.5%, 4.7%] |
| Maytag prices | 6.9% | 7.2% |
| | [5.1%, 8.7%] | [5.4%, 8.9%] |
| Whirlpool prices | 5.9% | 6.3% |
| | [3.9%, 7.8%] | [3.0%, 9.6%] |
| Consumer welfare | $-167M | $-224M |
| | [$-215M, $-119M] | [$-267M, $-182M] |
| *Employment* | | |
| Domestic jobs (w/o Maytag relocation) | -127 | -247 |
| | [-175, -79] | [-411, -82] |
| Domestic jobs (with Maytag relocation) | -735 | -1009 |
| | [-869, -601] | [-1188, -829] |

*Notes:* Ninety-five percent confidence intervals for the first column are computed from 200 residual bootstrap draws. Confidence sets for the second column are based on 50 fixed cost draws for each potential product.

changes, the varying production locations have no consumer impact but significantly affect employment. Holding pre-merger product portfolios fixed, a Whirlpool acquisition preserves 566 more domestic jobs than a Haier acquisition. Combining this result with Table 7 illustrates the relative magnitude of employment impacts clearly: with unchanged Maytag production locations, Whirlpool's acquisition results in a net loss of 127 U.S. jobs due to reduced output and substitution to foreign-produced competitor products. Allowing Whirlpool's observed production relocations increases this loss to 735 jobs. Conversely, allowing Haier's production adjustments reverses the sign, making Whirlpool's acquisition preferable for domestic employment by 566 jobs. Balancing this against the consumer welfare loss from Whirlpool's acquisition implies each preserved job must be valued at $293,000 per year to offset consumer harm (considering only U.S. consumer welfare and employment), or $150,000 when also accounting for industry profits.

Finally, I allow marginal costs to adjust based on production relocations, incorporating estimated labor and shipping costs from Table 5.[39] Without product portfolio adjustments, Whirlpool passes through 86 percent of marginal cost savings to consumers, while Haier passes through 85 percent. Importantly, although Whirlpool almost fully passes on the cost savings for relocated Maytag products, it simultaneously raises prices on unaffected Whirlpool products, reducing overall consumer gains. The pass-through rate therefore overstates the consumer benefits of cost savings after a Whirlpool acquisition.

Although relocating production from the U.S. to Mexico or China yields similar cost savings, Haier's complete offshoring to China results in an additional 6 percent marginal cost reduction across Maytag products relative to Whirlpool's partial offshoring, which maintains top-loader production in the United States. This widens the consumer welfare gap between the two scenarios.[40]

Additionally, cost reductions from offshoring slightly reduce U.S. jobs further—by 24 under Whirlpool and by 29 under Haier. When fully accounting for marginal cost changes, each preserved job under Whirlpool must now be valued at $376,000 annually to offset consumer harm (consumer welfare and jobs only), or $280,000 with industry profits.

With endogenous portfolio adjustments and offshoring cost changes, the difference in U.S. manufacturing jobs increases to 797. To offset consumer harm, each protected job needs to be worth at least $344,000 per year.

Depending on the assumptions made, the point estimates for the necessary job value

[39] Given the imprecise distance coefficient estimation in Table 5, I fix it at its point estimate across bootstrap draws. Appendix Table A.5 relaxes this constraint, yielding wider confidence intervals for offshoring-related estimates without affecting the main conclusions.

[40] Direct comparison in Table 8 isolates only relative differences. For total effects of offshoring, see Appendix Tables A.6 and A.7, comparing each acquisition scenario against no acquisition.

**Table 8:** Simulated effects of Maytag acquisitions by Whirlpool vs. Haier

| | **Pre-acquisition product portfolios** | | **Endogenous product portfolios** | |
|---|---|---|---|---|
| *Cost adjustments:* | None | Offshoring | None | Offshoring |
| *Cost pass-through* | | | | |
| Whirlpool relocation | – <br> – | 86% <br> [76%, 96%] | – <br> – | 85% <br> [84%, 87%] |
| Haier relocation | – <br> – | 85% <br> [72%, 98%] | – <br> – | 84% <br> [83%, 85%] |
| *Prices and consumer welfare* | | | | |
| Average price | 3.2% <br> [1.9%, 4.5%] | 4.6% <br> [2.0%, 7.3%] | 4.1% <br> [3.5%, 4.7%] | 5.5% <br> [4.7%, 6.2%] |
| Consumer welfare | $-166M <br> [$-213M, $-119M] | $-215M <br> [$-296M, $-133M] | $-222M <br> [$-264M, $-179M] | $-271M <br> [$-316M, $-225M] |
| *Employment* | | | | |
| Domestic jobs maintained | 566 <br> [400, 733] | 571 <br> [407, 734] | 754 <br> [559, 949] | 797 <br> [612, 982] |
| *Industry profits* | | | | |
| Variable profits | $81M <br> [$58M, $104M] | $55M <br> [$2M, $107M] | $79M <br> [$54M, $105M] | $47M <br> [$19M, $74M] |
| Total profits | $81M <br> [$58M, $104M] | $55M <br> [$2M, $107M] | $106M <br> [$80M, $132M] | $83M <br> [$56M, $111M] |
| *Maytag + Whirlpool profits* | | | | |
| Maytag cost change | – <br> – | 5.9% <br> [-4.3%, 16.0%] | – <br> – | 4.7% <br> [3.9%, 5.5%] |
| Variable profits | $23M <br> [$5M, $41M] | $-16M <br> [$-82M, $51M] | $4M <br> [$-37M, $44M] | $-38M <br> [$-81M, $6M] |
| Total profits | $23M <br> [$5M, $41M] | $-16M <br> [$-82M, $51M] | $40M <br> [$24M, $57M] | $11M <br> [$-5M, $26M] |
| *Value per job required to offset consumer welfare loss* | | | | |
| Consumer welfare only | $293k <br> [$209k, $377k] | $376k <br> [$229k, $524k] | $299k <br> [$203k, $396k] | $344k <br> [$250k, $438k] |
| Consumer welfare + total industry profits | $150k <br> [$90k, $211k] | $280k <br> [$59k, $502k] | $157k <br> [$100k, $213k] | $238k <br> [$172k, $304k] |

*Notes:* The first two columns compare the effect of a Maytag acquisition by Whirlpool with that of one by Haier without product portfolio adjustments. The final two columns account for endogenous portfolio adjustments. Columns (1) and (3) do not allow for acquisition-related cost changes. Columns (2) and (4) account for labor and shipping cost changes due to offshoring. Ninety-five percent confidence intervals for the first two columns are computed from 200 residual bootstrap draws. Confidence sets for final two columns are based on 50 fixed cost draws for each potential product.

to offset consumer harm range from $150,000 to $376,000 per year. However, these figures alone are insufficient to assess whether employment effects plausibly offset product market harm. Ideally, I would measure the full value of these jobs to local labor markets. Section 3 suggests these jobs are valuable, though average wages alone likely underestimate their value due to multiplier effects. To contextualize the estimates, I turn to prior studies on the local labor market value of multinational jobs and those assessing job values necessary to offset consumer losses from trade policies.

Setzler and Tintelnot (2021) find that each additional foreign multinational job increases the local labor market's total wage bill by $113,000 annually through direct and indirect local labor market effects. The literature on earnings losses of displaced workers after mass layoffs suggests that such earnings losses are persistent. For instance, Jacobson, LaLonde, and Sullivan (1993) find earnings losses of 40 percent in the short-term and 25 percent in the long-term using data from Pennsylvania in the 1970s and 1980s. Couch and Placzek (2010) reproduce this analysis for Connecticut (1993–2004) and find earnings losses of 32 percent short-term and 15 percent long-term. Similarly, Schmieder, Wachter, and Heining (2023) document long-term earnings losses of about 15 percent lasting at least 15 years following mass layoffs in Germany.

Alternatively, prior work evaluating U.S. sector-specific tariffs also provides valuable benchmarks. Hufbauer and Lowry (2012) estimate each job preserved by the 2011 safeguard tariffs on tire imports from China would need to be worth at least $900,000 annually to offset consumer losses, while Flaaen, Hortaçsu, and Tintelnot (2020) calculate that jobs created from the 2018 washing machine safeguard tariffs would need to be worth at least $817,000 per year.

Beyond wages, local job availability generates additional benefits, suggesting that the increase in the local wage bill from Setzler and Tintelnot (2021) is likely a lower bound for the full value of an appliance manufacturing job to the U.S. economy. Although this figure falls at the lower end of my estimated range, the magnitudes are comparable, indicating that domestic employment benefits from the Whirlpool acquisition are economically meaningful relative to consumer welfare losses.

Thus far, the analysis considered overall consumer and worker impacts. Yet, the distributional implications of the alternative acquisitions are also significant. While an additional thousand manufacturing jobs may not affect national employment or wages appreciably, Section 3 shows local impacts are substantial and persistent. Figure 1 highlights that washer manufacturing jobs are geographically concentrated in a small number of counties in Illinois, Iowa, Michigan, Ohio, and South Carolina.

Therefore, consumer harm from the merger is broadly dispersed nationwide, whereas employment benefits are highly concentrated geographically. If households exhibit diminishing marginal utility of income and job losses predominantly affect less affluent regions, a Whirlpool acquisition could yield a higher aggregate welfare (sum of domestic worker and consumer welfare) despite consumer welfare losses exceeding the wage gains. Additionally, accounting for nonwage outcomes related to employment—such as mental and physical health—further supports the case that Whirlpool's acquisition may offer superior overall domestic welfare relative to Haier's.

# 8 Conclusion

This paper provides a framework to quantify the trade-off that policy choices can generate between consumers and workers. To capture the incentives firms have to adjust their product portfolios in response to policy changes, I explicitly model endogenous portfolio decisions. To evaluate employment effects, I model the relationship between the product market equilibrium and labor demand. I find that incorporating product market responses is key to estimating employment effects.

I apply this framework empirically to analyze how foreign competition influences the consumer welfare and domestic employment effects of mergers. Specifically, I examine Whirlpool's acquisition of Maytag and compare its impacts to a hypothetical acquisition by Haier. I find that the Whirlpool acquisition significantly harmed consumers and that rivals had limited incentives to expand their product offerings. However, while an alternative Haier acquisition would have mitigated consumer harm, it would also have substantially increased domestic job losses. Finally, I calculate the necessary value of a domestic job to offset these consumer welfare losses, quantifying the trade-off explicitly.

The preceding analysis should not be viewed as an endorsement of allowing anticompetitive mergers to preserve domestic jobs. Such mergers still harm consumers (and foreign workers) and may hinder the efficient long-run reallocation of resources. Rather, the methodology developed here can help policymakers identify and evaluate mergers where employment impacts are particularly significant. Procompetitive merger enforcement could then be complemented by targeted labor market policies, such as the Trade Adjustment Assistance Program (see Hyman, Kovak, and Leive, 2023). Such an integrated approach could reconcile the interests of workers and consumers, making rigorous merger enforcement politically more viable.

# References


Arkolakis, Costas, Fabian Eckert, and Rowan Shi. 2023. "Combinatorial Discrete Choice: A Quantitative Model of Multinational Location Decisions." *NBER Working Paper 31877.*

Armington, Elizabeth, Eric Emch, and Ken Heyer. 2006. "The Year in Review: Economics at the Antitrust Division, 2005-2006." *Review of Industrial Organization* 29 (4): 305–326.

Ashenfelter, Orley C., Daniel S. Hosken, and Matthew C. Weinberg. 2013. "The Price Effects of a Large Merger of Manufacturers: A Case Study of Maytag-Whirlpool." *American Economic Journal: Economic Policy* 5 (1): 239–61.

Baker, Jonathan B., and Carl Shapiro. 2008a. "Detecting and Reversing the Decline in Horizontal Merger Enforcement." *Antitrust* 22 (3): 29–36.

———. 2008b. "Reinvigorating Horizontal Merger Enforcement," edited by Robert Pitofsky, 235–288. Oxford University Press.

Barboza, David. 2005. "From China, A New Bid for Maytag and Status." *New York Times,* https://www.nytimes.com/2005/06/22/business/worldbusiness/from-china-a-new-bid-for-maytag-and-status.html.

Benkard, C. Lanier, Ali Yurukoglu, and Anthony Lee Zhang. 2021. "Concentration in Product Markets." *NBER Working Paper 28745.*

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica* 63 (4): 841–890.

———. 2004. "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market." *Journal of Political Economy* 112 (1): 68–105.

Berry, Steven T., and Joel Waldfogel. 2001. "Do Mergers Increase Product Variety? Evidence from Radio Broadcasting*." *The Quarterly Journal of Economics* 116 (3): 1009–1025.

Caradonna, Peter, Nathan H. Miller, and Gloria Sheu. 2025. "Mergers, Entry, and Consumer Welfare." *American Economic Journal: Microeconomics* 17 (3): 103–130.

Ciliberto, Federico, Charles Murry, and Elie Tamer. 2021. "Market Structure and Competition in Airline Markets." *Journal of Political Economy* 129 (11): 2995–3038.

Couch, Kenneth A., and Dana W. Placzek. 2010. "Earnings Losses of Displaced Workers Revisited." *American Economic Review* 100 (1): 572–589.

Department of Justice. 2006. *Statement on the Closing of its Investigation of Whirlpool's Acquisition of Maytag.* Washington, DC: Author. https://www.justice.gov/archive/atr/public/press_releases/2006/215326.htm.

Draganska, Michaela, Michael J. Mazzeo, and Katja Seim. 2009. "Beyond plain vanilla: Modeling joint product assortment and pricing decisions." *Quantitative Marketing and Economics* 7 (2): 105–146.

Eizenberg, Alon. 2014. "Upstream Innovation and Product Variety in the U.S. Home PC Market." *The Review of Economic Studies* 81 (3): 1003–1045.

Fan, Ying. 2013. "Ownership Consolidation and Product Characteristics: A Study of the US Daily Newspaper Market." *American Economic Review* 103 (5): 1598–1628.

Fan, Ying, and Chenyu Yang. 2020. "Competition, Product Proliferation, and Welfare: A Study of the US Smartphone Market." *American Economic Journal: Microeconomics* 12 (2): 99–134.

———. 2025. "Estimating Discrete Games with Many Firms and Many Decisions: An Application to Merger and Product Variety." *Journal of Political Economy* 133 (6): 1886–1931.

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer. 2015. "The Next Generation of the Penn World Table." *American Economic Review* 105 (10): 3150–82.

Flaaen, Aaron, Ali Hortaçsu, and Felix Tintelnot. 2020. "The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines." *American Economic Review* 110 (7): 2103–27.

Garrido, Francisco. 2020. "Mergers Between Multi-Product Firms With Endogenous Variety: Theory and an Application to the RTE-Cereal Industry." *mimeo.*

Gathmann, Christina, Ines Helm, and Uta Schönberg. 2020. "Spillover Effects of Mass Layoffs." *Journal of the European Economic Association* 18 (1): 427–468.

Goldberg, Pinelopi Koujianou, and Frank Verboven. 2001. "The Evolution of Price Dispersion in the European Car Market." *The Review of Economic Studies* 68 (4): 811–848.

Goodman, Peter, and Ben White. 2005. "Haier Withdraws Maytag Bid." *Washington Post,* https://www.washingtonpost.com/archive/business/2005/07/20/haier-withdraws-maytag-bid/f05586dd-097d-41b8-8cee-99c3bd17a72b/.

Grieco, Paul L.E., Charles Murry, and Ali Yurukoglu. 2024. "The Evolution of Market Power in the Us Auto Industry." *Quarterly Journal of Economics* 139 (2): 1201–1250.

Hufbauer, Gary, and Sean Lowry. 2012. "US Tire Tariffs: Saving Few Jobs at High Cost." *Peterson Institute for International Economics.*

Hyman, Benjamin, Brian Kovak, and Adam Leive. 2023. "Wage Insurance for Displaced Workers." *Working Paper.*

Igami, Mitsuru. 2018. "Industry Dynamics of Offshoring: The Case of Hard Disk Drives." *American Economic Journal: Microeconomics* 10 (1): 67–101.

Imbens, Guido, and Charles Manski. 2004. "Confidence Intervals for Partially Identified Parameters." *Econometrica* 72 (6): 1845–1857.

Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan. 1993. "Earnings Losses of Displaced Workers." *American Economic Review* 83 (4): 685–709.

Jeziorski, Przemislaw. 2015. “Empirical Model of Dynamic Merger Enforcement–Choosing Ownership Caps in US Radio.” *mimeo.*

Kroft, Kory, Yao Luo, Magne Mogstad, and Bradley Setzler. 2025. “Imperfect Competition and Rents in Labor and Product Markets: The Case of the Construction Industry.” *American Economic Review* 115 (9): 2926–69.

Lee, Robin S., and Ariel Pakes. 2009. “Multiple Equilibria and Selection by Learning in an Applied Setting.” *Economics Letters* 104 (1): 13–16.

Li, Sophia, Joe Mazur, Yongjoon Park, James Roberts, Andrew Sweeting, and Jun Zhang. 2022. “Repositioning and Market Power After Airline Mergers.” *The RAND Journal of Economics* 53 (1): 166–199.

Marinescu, Ioana, and Herbert Hovenkamp. 2019. “Anticompetitive Mergers in Labor Markets.” *Indiana Law Journal* 94 (3): 1031.

Maytag. 2005. *2004 Annual Report.* Newton, IA: Author.

Mazzeo, Michael J. 2002. “Product Choice and Oligopoly Market Structure.” *The RAND Journal of Economics* 33 (2): 221–242.

Muendler, Marc-Andreas, and Sascha O. Becker. 2010. “Margins of Multinational Labor Substitution.” *American Economic Review* 100 (5): 1999–2030.

Noble, Breana. 2021. “Stellantis CEO says PSA-FCA merger is a ’shield’ for auto jobs, but doesn’t rule out cuts.” *The Detroit News,* https://www.detroitnews.com/story/business/autos/chrysler/2021/01/19/stellantis-ceo-carlos-tavares-says-psa-fca-merger-shield-auto-jobs/4203304001/.

OECD. 2016. “Public Interest Considerations in Merger Control.” *DAF/COMP/WP3 /WD(2016)30.*

Pakes, A., J. Porter, K. Ho, and J. Ishii. 2015. “Moment Inequalities and Their Application.” *Econometrica* 83 (1): 315–334.

Prager, Elena, and Matt Schmitt. 2021. “Employer Consolidation and Wages: Evidence from Hospitals.” *American Economic Review* 111 (2): 397–427.

Schmieder, Johannes, Till von Wachter, and Joerg Heining. 2023. “The Costs of Job Displacement over the Business Cycle and Its Sources: Evidence from Germany.” *American Economic Review* 113 (5): 1208–1254.

Seim, Katja. 2006. “An Empirical Model of Firm Entry with Endogenous Product-Type Choices.” *The RAND Journal of Economics* 37 (3): 619–640.

Setzler, Bradley, and Felix Tintelnot. 2021. “The Effects of Foreign Multinationals on Workers and Firms in the United States.” *The Quarterly Journal of Economics* 136 (3): 1943–1991.

Shapiro, Carl. 2019. “Protecting Competition in the American Economy: Merger Control, Tech Titans, Labor Markets.” *Journal of Economic Perspectives* 33 (3): 69–93.

Sweeting, Andrew. 2010. "The Effects of Mergers on Product Positioning: Evidence From the Music Radio Industry." *RAND Journal of Economics* 41 (2): 372–397.

Tintelnot, Felix. 2017. "Global Production With Export Platforms." *The Quarterly Journal of Economics* 132 (1): 157–209.

Wollmann, Thomas G. 2018. "Trucks without Bailouts: Equilibrium Product Characteristics for Commercial Vehicles." *American Economic Review* 108 (6): 1364–1406.

# Online Appendix to:

## "Mergers, Foreign Competition, and Jobs: Evidence from the U.S. Appliance Industry"

Felix Montag

This version: April 30, 2026

# I Appendix to Section 2: Data Set Construction

## I.A Product market data set

This appendix provides further details on the construction of the product market data set.

**Product data.** As described in Section 2, I define a washing machine product by the combination of brand, retailer, and washer type: front-loader, regular top-loader (with an agitator), or high-efficiency top-loader (without an agitator). These characteristics primarily differentiate products.

Figure A.1 illustrates the key difference between front-loaders, which are loaded from the front, and top-loaders, which are loaded from above. Front-loaders can be stacked (e.g., placing a dryer on top), are more water- and energy-efficient, offer better cleaning performance, and typically cost more. Top-loaders cannot be stacked; however, among top-loaders, a critical distinction is the presence of an agitator, as shown in Figure A.2. Top-loaders without agitators, known as high-efficiency top-loaders, perform better than regular top-loaders in terms of efficiency and cleaning, but not as well as front-loaders.[41]

Within each market (defined nationally at the yearly level), I group survey responses based on these three characteristics.[42] This yields 2,939 products from 2005 to 2015. Under this definition, many products have small market shares, often based on a single household's response. Additionally, responses sometimes lack brand information. Thus, I exclude products labeled as "Other Brands" or "Store Brand/Generic," and any product with a market volume share below 0.01 percent. This reduces the data set to 1,590 products, which still represent between 97.3 and 99.0 percent of total washing machine sales volume in the *TraQline* data, ensuring minimal selection bias.

[41] See, for example, McCabe (2016) for a detailed comparison of washer types.

[42] I classify Maytag products as Whirlpool products in the first quarter of 2006, before the official acquisition, to avoid artificially inflating the number of washing machine products that year. Given that merger discussions were public from mid-2005 onward, it is reasonable to assume minimal competitive interaction between Maytag and Whirlpool by early 2006.

**Figure A.1:** Difference between front-loader and top-loader

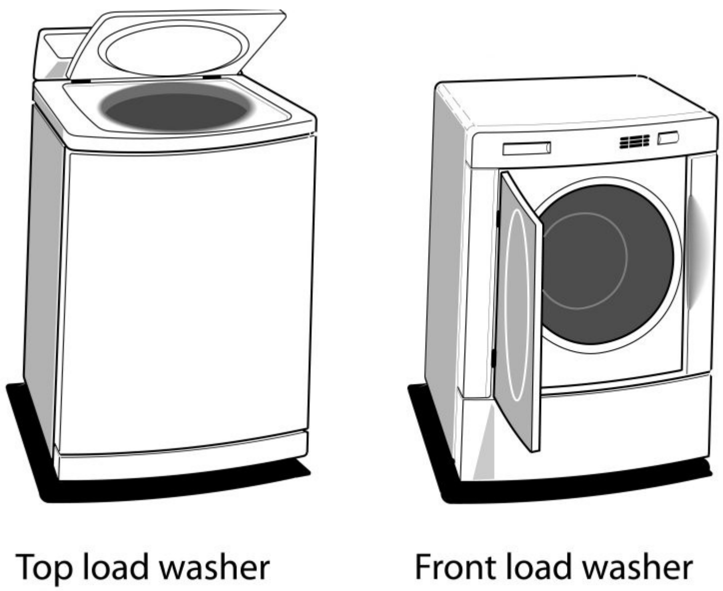
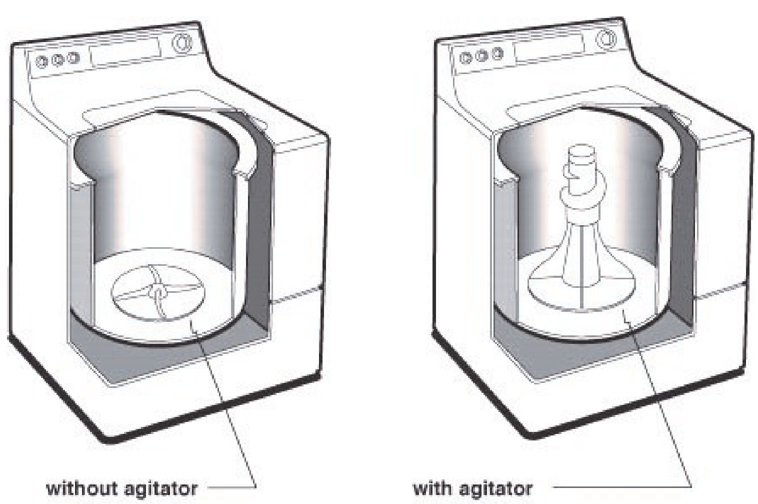



**Figure A.2:** Top-loaders with and without agitator



For characteristics collected only from a random subset of *TraQline* respondents (whether a washer is part of a stacked pair; has a stainless steel, white, or other-colored exterior; is Energy Star certified; includes additional noise insulation or a child lockout; and the number of special programs), I use the within-group average response.

**Household income.** The CPS data include exact household incomes, whereas the *TraQline* data only report income ranges. To estimate the relationship between price sensitivity and household income using a single parameter, I assign exact income values to each household based on the empirical income distribution and reported ranges, proceeding as follows:

1. Compute midpoints of the nonoverlapping income ranges reported for each respondent.

2. For each year, fit a log-normal distribution to the set of midpoint values.

3. Draw 1,000,000 random incomes from this fitted log-normal distribution.

4. Allocate each drawn income to the corresponding reported income bucket.

5. For each household, randomly draw (with replacement) an income value from the set of incomes matching its income bucket.

## I.B Plant locations and plant location weights

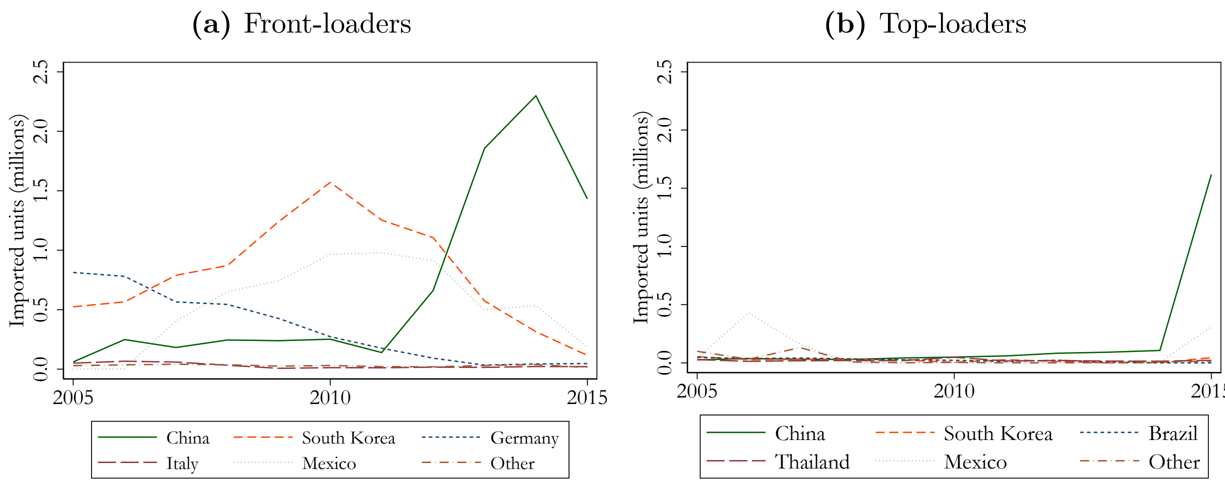
**Plant locations.** Constructing the dataset on washing machine manufacturing plants involves three steps. First, I identify plant locations from annual reports, news articles, and transcripts from the USITC's antidumping hearings on washing machine imports from Mexico and South Korea.

For LG and Samsung, pre-2012 production locations primarily rely on the USITC investigation. For 2012–2015, I use firm-level washer imports based on PIERS shipping data, as documented in Flaaen, Hortaçsu, and Tintelnot (2020). For Electrolux, Maytag, and Whirlpool, plant locations come largely from their annual reports. Since General Electric's annual reports lack detailed appliance plant information, I combine USITC documents and news reports to identify its plant locations.

Second, to confirm which plants supplied the U.S. market, I cross-check these locations against USITC data on front- and top-loading washer imports by country, excluding plants that cannot plausibly produce substantial volumes for the U.S. market.

Finally, I validate that each significant source country's washing machine exports to the U.S. correspond plausibly to the identified plants. Figure A.3 illustrates the evolution of annual U.S. imports of front- and top-loaders by country. Over half of the front-loaders sold in the U.S. during this period were imported. Initially, Germany was the primary exporter, reflecting Whirlpool's Schorndorf plant, which closed in 2012. Before 2012, LG and Samsung imported primarily from South Korea and Mexico. Following antidumping duties in 2012, imports from these countries declined, shifting LG and Samsung production to China (see Flaaen, Hortaçsu, and Tintelnot (2020) for details). In contrast, significant top-loader imports into the U.S. began only after 2011, primarily from China, driven by LG and Samsung's increased market presence.

**Figure A.3:** Washer imports to the United States by source country



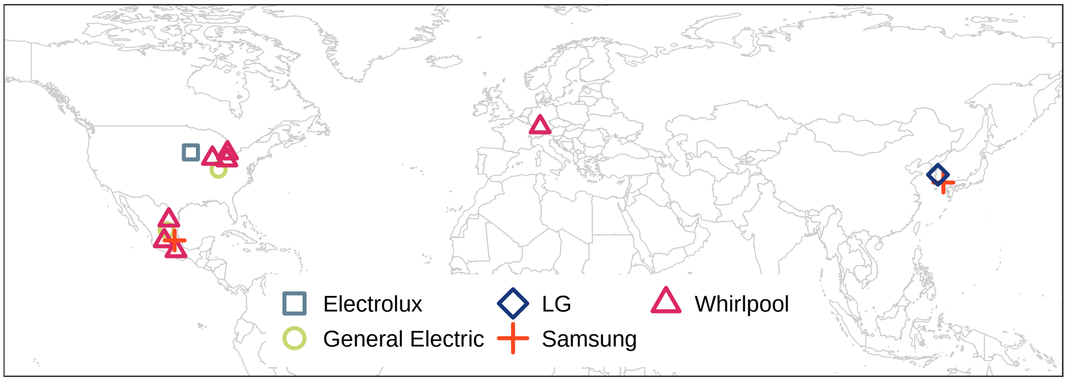

*Notes:* The left panel plots annual U.S. import volumes of front-loader washers (HS8450110080, HS8450200080, HS8450200090) by source country. The right panel plots annual U.S. import volumes of top-loader washers (HS8450110040, HS8450200040) by source country. Both panels show the top six source countries, grouping all others into "Other".

For reference, according to Appliance Portrait (2006), approximately 9.3 million washers were sold in the U.S. in 2005. Based on the *TraQline* data, about one-third of these were front-loaders, with the remainder being top-loaders. The front-loader share rose to over 40 percent by 2010 and then declined to approximately 25 percent by 2015. Although significant numbers of front-loaders were imported throughout the period, most top-loaders were produced domestically.

Figures A.4, A.5, and A.6 display washer plant locations for manufacturers holding more than 3 percent of the U.S. market volume in any year during the sample period.

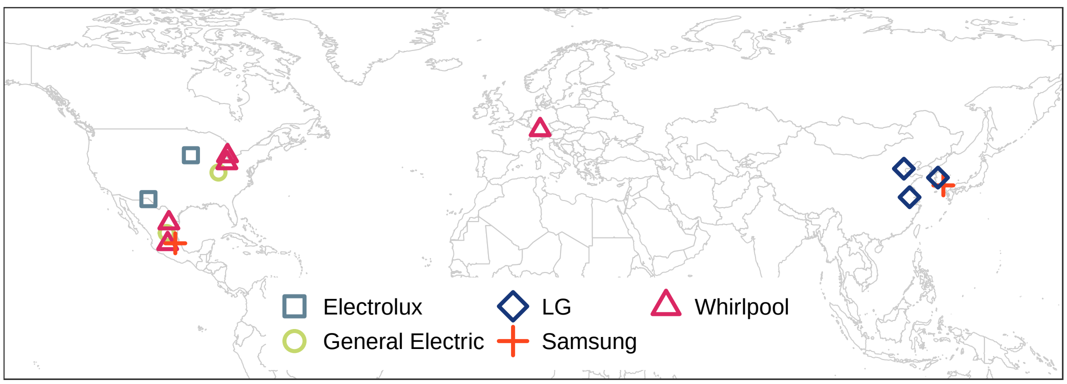
**Plant location weights.** Table A.1 reports the weights used to compute product-level average real exchange rates, indicating the share of each product sourced from different countries annually. Weights are based on identified plant locations, aggregate USITC import data, and firm-level washer imports (2012–2015) from PIERS data reported in Flaaen, Hortaçsu, and Tintelnot (2020).

**Figure A.4:** Washer plants manufacturing for the U.S. market, 2007



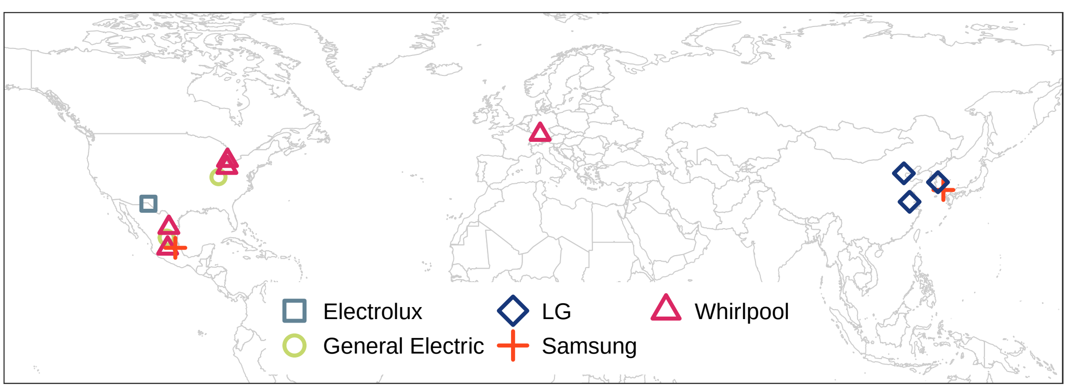

*Notes:* The map displays all plants manufacturing washing machines for the U.S. market in 2007, for manufacturers with a market share exceeding 3 percent in any year of the sample period.

**Figure A.5:** Washer plants manufacturing for the U.S. market, 2009




*Notes:* The map displays all plants manufacturing washing machines for the U.S. market in 2009, for manufacturers with a market share exceeding 3 percent in any year of the sample period.

**Figure A.6:** Washer plants manufacturing for the U.S. market, 2011




*Notes:* The map displays all plants manufacturing washing machines for the U.S. market in 2011, for manufacturers with a market share exceeding 3 percent in any year of the sample period.

**Table A.1:** Plant location weights

| Owner | Brand | Product | Years | China | Germany | Mexico | South Korea | USA |
|---|---|---|---|---|---|---|---|---|
| Electrolux | All brands | Front-Loader | 2005–2007 | | | | | 1 |
| Electrolux | All brands | Front-Loader | 2008–2015 | | | 1 | | |
| Electrolux | All brands | Top-Loader | 2005–2010 | | | | | 1 |
| Electrolux | All brands | Top-Loader | 2011–2015 | | | 1 | | |
| General Electric | All brands | Front-Loader | 2005–2012 | | | 1 | | |
| General Electric | All brands | Front-Loader | 2013–2015 | | | | | 1 |
| General Electric | All brands | Top-Loader | 2005–2015 | | | | | 1 |
| Whirlpool | Roper | Front-Loader | 2005–2007 | | | | | 1 |
| Whirlpool | All other WP brands | Front-Loader | 2005–2007 | | 1 | | | |
| Whirlpool | All other WP brands | Front-Loader | 2008–2010 | | 0.5 | 0.5 | | |
| Whirlpool | All other WP brands | Front-Loader | 2011–2012 | | 0.33 | 0.33 | | 0.33 |
| Whirlpool | All brands | Front-Loader | 2013–2015 | | | | | 1 |
| Whirlpool | Admiral, Amana, Maytag | Front-Loader | 2007–2010 | | | 1 | | |
| Whirlpool | Admiral, Amana, Maytag | Front-Loader | 2011–2012 | | | 0.5 | | 0.5 |
| Whirlpool | All brands | Top-Loader | 2005–2015 | | | | | 1 |
| LG | All brands | Front-Loader | 2005–2012 | | | | 1 | |
| LG | All brands | Front-Loader | 2013 | 0.67 | | | 0.33 | |
| LG | All brands | Front-Loader | 2014–2015 | 1 | | | | |
| LG | All brands | Top-Loader | 2005–2007 | | | | 1 | |
| LG | All brands | Top-Loader | 2008–2015 | 1 | | | | |
| Samsung | All brands | Front-Loader | 2005–2011 | | | 0.5 | 0.5 | |
| Samsung | All brands | Front-Loader | 2012 | 0.33 | | 0.33 | 0.33 | |
| Samsung | All brands | Front-Loader | 2013–2015 | 1 | | | | |
| Samsung | All brands | Top-Loader | 2005–2011 | | | | 1 | |
| Samsung | All brands | Top-Loader | 2012–2015 | 1 | | | | |
| Maytag | All brands | Front-Loader | 2005–2006 | | | | | 1 |
| Maytag | All brands | Top-Loader | 2005–2006 | | | | | 1 |

**Plant-level data on output and employment.** Data on employment and output at Whirlpool's Clyde, Ohio, and Schorndorf, Germany plants (producing for the U.S. market), and Radomsko, Poland (producing for Europe), are sourced from news reports. Data on Whirlpool's Amiens, France, and Poprad, Slovakia plants are from case studies by Ferencikova (2002) and Rubens, Ferencikova, and Bardy (2019), who cooperated with Whirlpool Slovakia to obtain data on employment and output. Data for BSH plants in Berlin, Germany, and Alcalá, Spain, originate from historical internal documents obtained from the BSH company archive.

## I.C Details on the instrumental variable for price

Figure A.7 illustrates the evolution and source of variation in the deflated average real exchange rate. The left panel plots the average deflated RER across all production locations by manufacturer. This average is computed using the country-level RER of each manufacturer's plants, plant-level production shares, and sales volume weights, all deflated to 2012 U.S. dollars. Although this plot aggregates across products of a manufacturer, significant variation remains over time. The right panel separates the average RER into top-loaders and front-loaders for Whirlpool and Maytag products, highlighting within-manufacturer variation.[43] For example, while Maytag and Whirlpool top-loaders were consistently produced in the U.S., front-loaders were sourced from multiple locations, including Mexico and Germany.

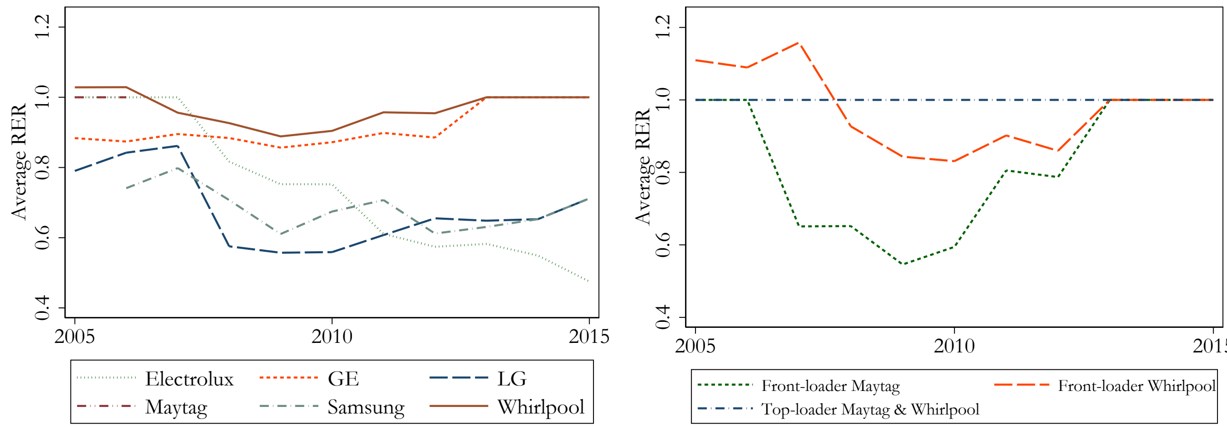
The substantial variation in RER over time aligns with anecdotal evidence on the strategic importance of production location costs. Maytag's financial struggles before the merger were partly attributed to high domestic production costs and limited offshoring.[44] Similarly, Electrolux implemented a global cost-reduction initiative in 2004, aiming to relocate over half of its production to lower-cost countries by 2009 (Electrolux, 2007). These examples underscore the relevance of international production decisions in driving costs in the appliance market, illustrating the source of variation used in the instrument: fluctuations in RER between the U.S. and specific production locations and shifts in plant locations.

[43] Maytag products include Admiral, Amana, Magic Chef, and Maytag brands; Whirlpool products include all other Whirlpool-owned brands.

[44] Maytag's 2004 annual report explicitly highlighted these pressures: "Globalization of manufacturing is allowing companies to reduce costs by reaching around the world farther, faster and cheaper than ever before. It's no longer a trend we can watch with interest but a reality to which we are responding" (Maytag, 2005, p. 3).

**Figure A.7:** Average real exchange rate over time

**(a)** RER by manufacturer **(b)** RER by product of merging parties




*Notes:* The left panel plots the average deflated RER of production locations by manufacturer over time for manufacturers with at least a 3 percent market share in any year. The right panel plots this RER separately for Maytag and Whirlpool products, based on their respective production locations and plant-level shares. Maytag products include Admiral, Amana, Magic Chef, and Maytag brands; Whirlpool products cover all other Whirlpool-owned brands.

# II Appendix to Section 3: Descriptive Results

## II.A Additional descriptive results on price effects of the merger

To ensure comparability of my descriptive results to the analysis in Ashenfelter, Hosken, and Weinberg (2013) and to provide evidence on dryers, I replicate the event study using freestanding ranges in the U.S. as a control market.[45] This serves as a suitable control if washer and dryer prices would have evolved similarly to freestanding ranges absent the merger.

Figure A.8 displays the estimated event study from Equation 1 using freestanding ranges as the control. Two main insights emerge: first, washers and dryers exhibit similar price dynamics; second, washer and dryer prices do not increase relative to ranges.

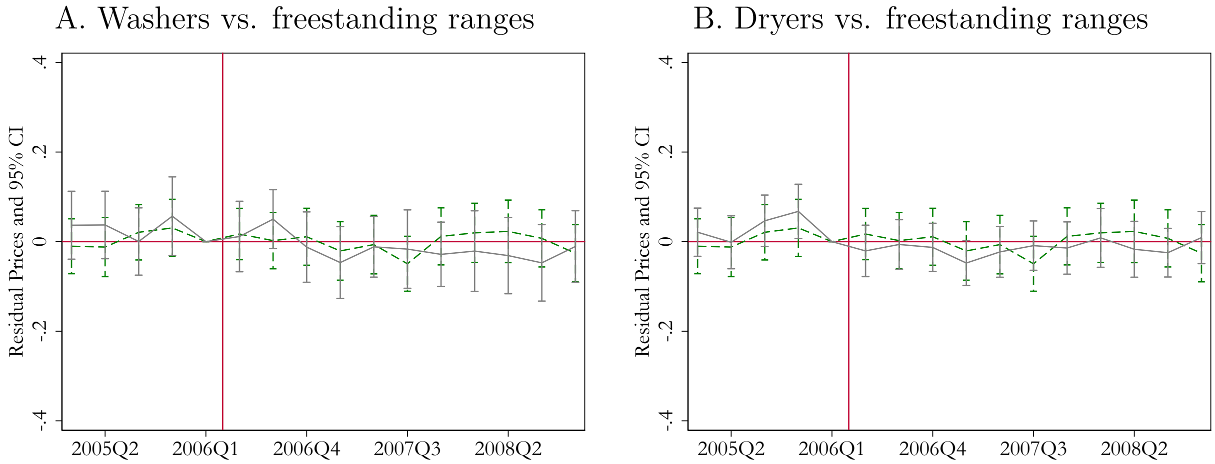
To further understand the merger's effects, I separately estimate price differences around the merger for Maytag and Whirlpool products using freestanding ranges as the control. Specifically, I estimate:

$$log(p_{it}) = \alpha_1 \text{Maytag}_{it} \times \text{post}_t + \alpha_2 \text{Whirlpool}_{it} \times \text{post}_t + \beta x_{it} + \tau_i + \gamma_t + \epsilon_{it}\,. \tag{19}$$

Here, $\alpha_1$ captures the average price effect for Maytag products and $\alpha_2$ for Whirlpool products.

[45] Ashenfelter, Hosken, and Weinberg (2013) use ranges, cooktops, ovens, and freezers as control group.

**Figure A.8:** Price effects of the merger for washers and dryers




*Notes:* The figure shows the residualized logarithm of prices for Maytag and Whirlpool washers and dryers in the United States compared to freestanding ranges from other manufacturers, unaffected by the merger. The solid line depicts the residualized price evolution for washers and dryers; the dashed line represents the control group (freestanding ranges). The merger occurred at the end of 2006Q1, normalized to zero. Confidence bounds are at the 95 percent level, with standard errors clustered at the model level.

Following Ashenfelter, Hosken, and Weinberg (2013), I restrict the observation period from 2005Q2 to 2008Q3, noting that I use quarterly instead of monthly data.

Table A.2 summarizes these price changes. Columns (1) and (4) pool Maytag and Whirlpool products and indicate no average price increase for washers or dryers. Columns (2) and (5) report separate estimates for Maytag and Whirlpool products. Columns (3) and (6) replicate these estimates with more granular product fixed effects instead of brand fixed effects. The results consistently suggest no price increase and possibly price decreases for Maytag and Whirlpool washers and dryers compared to freestanding ranges.

Comparing washers to ranges, Ashenfelter, Hosken, and Weinberg (2013) report price declines for old and new Whirlpool washers and no price changes for old and new Maytag washers. While direct reconciliation is limited by differences in data sources and the fact that *TraQline* does not allow me to control for product age to distinguish between old and new products, my results align broadly with their findings.

For dryers, Ashenfelter, Hosken, and Weinberg (2013) report price increases for new Whirlpool dryers, decreases for old Whirlpool dryers, no change for old Maytag dryers, and a modest increase for new Maytag dryers. Depending on the relative importance of new vs. old dryers, these results may align with each other.

However, interpreting these findings as causal evidence that Whirlpool's acquisition of Maytag did not affect laundry product prices would likely be erroneous. Comparisons of U.S. washer prices to prices in other similar international markets, unaffected by the merger, strongly suggest that U.S. prices would have fallen in the absence of the merger. Therefore,

**Table A.2:** Price evolution for laundry products relative to freestanding ranges

| | Washers vs. ranges | | | Dryers vs. ranges | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Merging parties × post | -0.020 | | | -0.038 | | |
| | [-0.080, 0.040] | | | [-0.089, 0.012] | | |
| Maytag × post | | -0.024 | -0.037* | | -0.036 | -0.018 |
| | | [-0.076, 0.029] | [-0.078, 0.003] | | [-0.099, 0.026] | [-0.068, 0.032] |
| Whirlpool × post | | -0.017 | -0.014 | | -0.040 | -0.002 |
| | | [-0.094, 0.059] | [-0.050, 0.023] | | [-0.098, 0.017] | [-0.055, 0.051] |
| Characteristics controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter × year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Brand fixed effects | Yes | Yes | No | Yes | Yes | No |
| Product fixed effects | No | No | Yes | No | No | Yes |
| Observations | 2114 | 2114 | 1972 | 5011 | 5011 | 4636 |

Notes: Columns (1) to (3) compare the logarithm of prices for washers and freestanding ranges. Columns (4) to (6) compare the logarithm of prices for dryers and freestanding ranges. The differences in observations in Columns (3) and (6) from the preceding columns are due to the iterative dropping of singleton observations in the clustering of standard errors. Ninety-five percent confidence intervals are reported in parentheses. Standard errors are clustered at brand level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

freestanding ranges may be influenced by distinct industry dynamics and thus may not be an appropriate control for washers and dryers in this context.

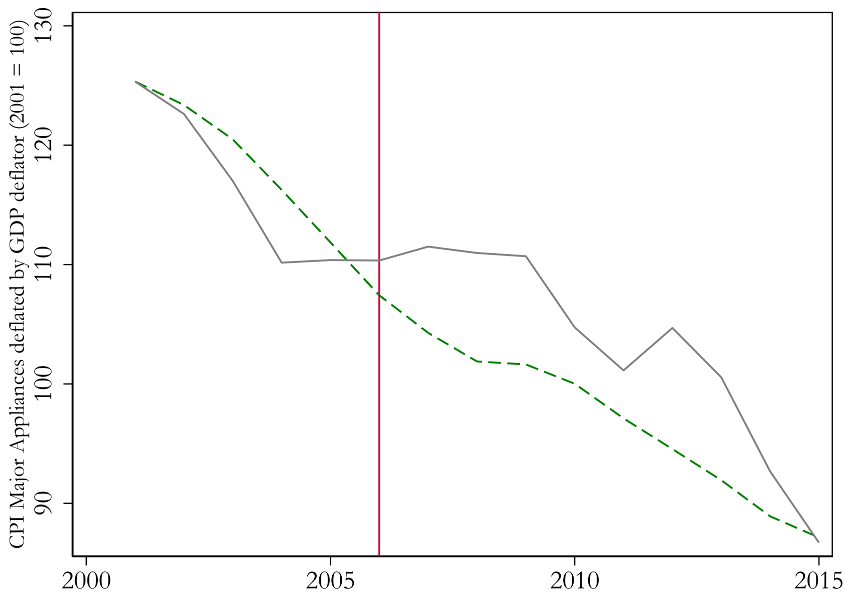
Since pre-treatment price data begin only in 2005, just prior to the merger, one might question how appropriate washer prices in the European Union are as a control for U.S. washer prices. Although a specific consumer price index (CPI) for washing machines is unavailable, comparing the CPIs for major appliances in the U.S. and household appliances in the European Union offers insight into broader trends.

Figure A.9 illustrates this comparison. Consistent with the descriptive evidence in Section 3 and anecdotal reports, deflated appliance prices declined in both the U.S. and EU prior to Whirlpool's acquisition of Maytag. Beginning in 2005, when merger negotiations commenced, this downward trend halted in the U.S., whereas prices continued to decline in the EU. After 2010, deflated prices in the U.S. resumed their decline.

## II.B Additional descriptive results on product entry

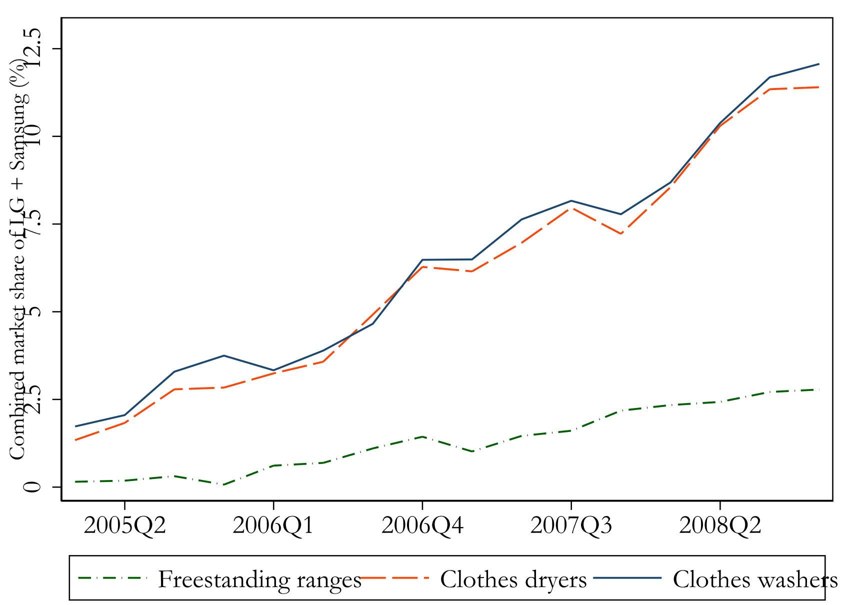
Figure A.10 illustrates the combined U.S. market share of LG and Samsung for washers, dryers, and freestanding ranges. Between 2005 and 2008, LG and Samsung significantly expanded their share for washers and dryers—from approximately 2 percent to about 12 percent. In contrast, their combined market share for freestanding ranges remained low, reaching only about 2 percent by the end of 2008.

**Figure A.9:** Consumer price index for major appliances in the U.S. and the EU




*Notes:* The figure compares consumer price indices for major appliances in the U.S. and the European Union from 2001 to 2015, deflated by the U.S. GDP deflator. Both indices are normalized to 100 in 2001. The solid line represents the United States, and the dashed line represents the European Union.

**Figure A.10:** Combined LG and Samsung market share by appliance

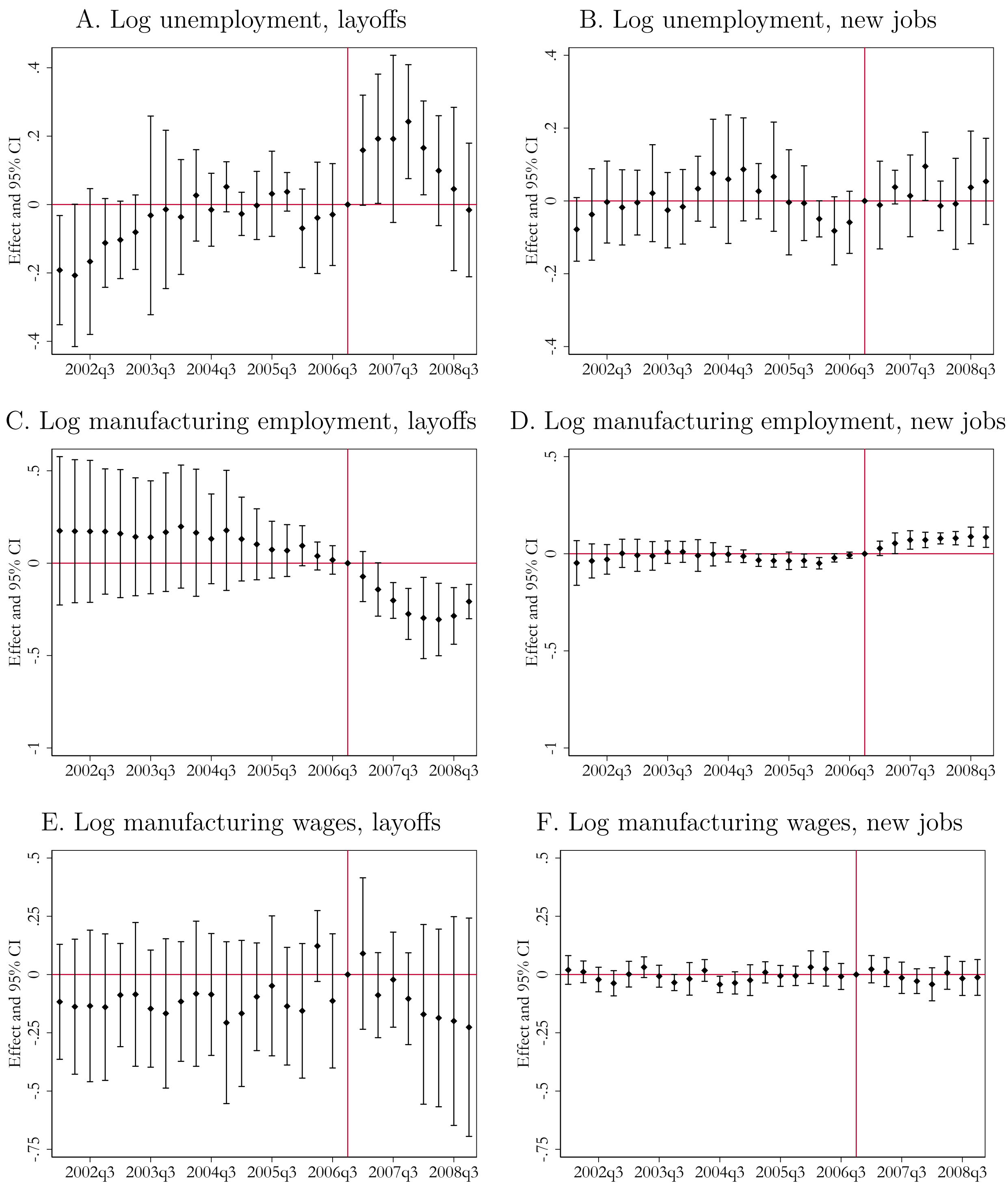



*Notes:* The figure showss the combined market share (volume sales) evolution in the U.S. and key European control markets for 2005 to 2008.

## II.C Additional descriptive results on mass layoffs and new jobs

Figure A.11 presents event study plots illustrating the local labor market effects of mass layoffs and new job creation following the merger. The outcomes analyzed are county-level unemployment, manufacturing employment, and manufacturing wages. The key outcomes exhibiting significant treatment effects in the main analysis—specifically, unemployment and manufacturing employment following mass layoffs, and manufacturing employment following new job creation—do not display pre-treatment trends. This strengthens the robustness of the main findings.

**Figure A.11:** Effects of mass layoffs and new jobs over time




*Notes:* The figure shows the quarterly changes in labor market outcomes for counties experiencing mass layoffs or job creation at Whirlpool plants relative to matched control counties. Panels A, C, and E depict effects from the closure of Maytag manufacturing plants and headquarters; Panels B, D, and F depict effects from new job creation at existing Whirlpool plants. Standard errors are clustered at the county level.

# III Appendix to Section 4: Model Details

## III.A Plant-level output and employment

To test for economies of scale in labor, I specify a Cobb-Douglas relationship between plant-level output and employment.[46] Specifically, I assume that plant-level output ($q_{c(j)t}$) relates to employment ($L_{c(j)t}$) via:

$$q_{c(j)t} = AL^{\zeta}_{c(j)t}.$$

I estimate the parameters by regressing the log of annual plant-level output on the log of plant-level manufacturing employment:

$$\ln(q_{c(j)t}) = \ln(A) + \zeta \ln(L_{c(j)t}) + \eta_{c(j)t}, \tag{20}$$

where $\eta_{c(j)t}$ represents an error term that occurs because firms hire workers before observing transitory shocks, thus knowing only $E\left[q_{jt}\right]$, not $q_{jt}$ itself.

Table A.3 shows the estimates. Although the sample size is small, I cannot reject the hypothesis that the elasticity of output with respect to labor is equal to one. This finding indicates constant returns to scale in labor.

[46] Nesting a Cobb-Douglas production function for labor within a Leontief production function is similar to the approach taken by Loecker and Scott (2024) who model the production of beer.

**Table A.3:** Relationship between annual plant-level output and employment

| | (1) | (2) |
|---|---|---|
| Constant | 6.40*** | 6.23*** |
| | [4.61, 8.18] | [4.28, 8.18] |
| Logarithm of plant-level employment | 1.11*** | 1.15*** |
| | [0.84, 1.38] | [0.87, 1.43] |
| Restrict to 2000s | No | Yes |
| Observations | 25 | 12 |

*Notes:* The dependent variable is the logarithm of plant-level output. Column (2) restricts observations to the years 2000–2009. 95% confidence intervals are reported in brackets. Significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# IV Appendix to Section 5: Estimation Details

## IV.A Estimating product characteristics for potential products

Potential products include both the products brand owners actually offer (active products) and those they could offer but do not (inactive products). Active products are observed directly in the data. Estimating characteristics of inactive products is more complex.

The analysis focuses on products firms are already technologically capable of producing. Thus, if a firm does not sell front-loading washers, these are not potential products. For example, if Maytag sells regular top-loaders under its Amana brand at Best Buy and Lowe's, similar Amana top-loaders at other major retailers are potential but inactive products.[47]

Characteristics of products can vary slightly across retailers. For instance, Amana top-loaders sold at Best Buy might differ somewhat from those sold at Lowe's. To attribute characteristics to an inactive product—such as Amana regular top-loaders potentially sold at Sears—I must decide whether to use characteristics from the Amana top-loaders actually sold at Best Buy or Lowe's.

Whenever a particular combination of brand and key characteristic exists at two or more retailers, I use the most similar retailer, using the following ordering:

- **Sears**: Home Depot, Lowe's, Best Buy, H.H. Gregg, Others
- **Home Depot**: Lowe's, Sears, Best Buy, H.H. Gregg, Others
- **Lowe's**: Home Depot, Best Buy, Sears, H.H. Gregg, Others

[47]Major retailers are Best Buy, H.H. Gregg, Home Depot, Lowe's, and Sears.

- **Best Buy**: Lowe's, H.H. Gregg, Home Depot, Sears, Others
- **H.H. Gregg**: Best Buy, Lowe's, Home Depot, Sears, Others

## IV.B Details on demand estimation

Following Berry, Levinsohn, and Pakes (2004), I estimate demand in two stages. First, I solve for the nonlinear parameters $\theta_2 = (\alpha, \kappa_\alpha, \sigma^{\mathrm{FL}})$ and corresponding mean utilities $\delta$, obtaining $\hat{\theta}_2$ and $\hat{\delta}$. Second, I recover the linear taste parameters $\beta$. Throughout, I implement best practices as described by Conlon and Gortmaker (2020). For simplicity, the market index $t$ is omitted; all expressions refer to a single market and are averaged subsequently.

The estimation of the nonlinear parameters and the mean utilities proceeds in two iterative steps. In the inner loop, I search for the mean utilities given a guess of the nonlinear parameters. In the outer loop, I search for the nonlinear parameters that minimize the objective function, solving the inner loop at each step.

To estimate the mean utilities $\delta$, I follow Berry (1994) and invert the market share function $s_j(\delta_j; \theta)$ to obtain $\delta_j(s_j^n, s_j(\delta_j; \theta))$, where $s_j^n$ denotes the market shares observed in the data and $s_j(\delta_j; \theta)$ denotes the simulated market shares implied by the model and the parameter vector $\theta$.[48] Second, I use the fixed-point formulation from Berry, Levinsohn, and Pakes (1995) to estimate $\hat{\delta}_j$. I use the SQUAREM described in Reynaerts, Varadha, and Nash (2012) to accelerate the convergence of the fixed-point iterations. As convergence is not guaranteed, whenever it fails, I revert to the contraction mapping in Berry, Levinsohn, and Pakes (1995), which has guaranteed convergence. Finally, I speed up the inversion of market shares by using the reformulation of the contraction mapping in terms of consumer-specific choice probabilities for the outside option, described by Brunner et al. (2020).

To approximate model-predicted market shares from Equation 12, I integrate numerically by Monte Carlo simulation, drawing 2,000 households per market from the joint empirical distribution of demographics (from CPS data) and standard-normal distributed unobserved taste shocks (via scrambled Halton draws as in Owen, 2017).

Estimation relies on three moment conditions:

**1. Income-price covariance:** Matches the covariance between the first-choice washer's price and average income of households purchasing it:

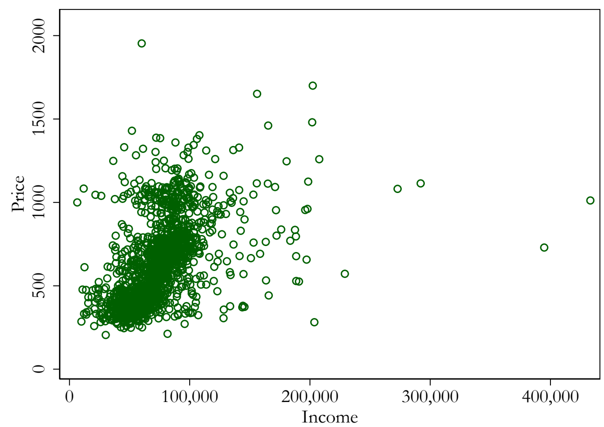
$$m_1(\theta) = \sum_j \frac{n_j}{n} p_j \left\{ \frac{1}{n_j} \sum_{i: y_i^1 = j} \iota_i - E\left[\iota \mid y^1 = j, \theta\right] \right\}, \tag{21}$$

[48]Note that $s_j(\delta_j; \theta)$ also depends on the product and household characteristics, which I omit to simplify notation.

where $n_j$ is the number of buyers of product $j$, $y_i^1$ is household $i$'s chosen product, $p_j$ is product $j$'s price, and $\iota_i$ denotes household $i$'s income. Figure A.12 illustrates this relationship.

Figure A.12 shows a scatter plot of the relationship between household income and price.

**Figure A.12:** Correlation of average purchaser household income and price by product




Notes: The plot shows the average annual income of households purchasing a particular washer on the x-axis and the average price of that washer on the y-axis. Each point is a product in a particular year.

**2. Front-loader substitution pattern:** Matches the covariance between choosing a front-loader and the share of front-loaders in the second-choice brand:

$$m_2(\theta) = \sum_j \frac{n_j}{n} x_j^{FL} \sum_{b' \neq b_j} x_{b'}^{FL} \left\{ \frac{n_{jb'}}{n_j} - E\left[\mathbb{1}(b^2 = b') \mid y^1 = j, \theta\right] \right\}, \tag{22}$$

where $b_j$ denotes brand of product $j$, $b^2$ is the second-choice brand, and $x_j^{FL}$ ($x_{b'}^{FL}$) indicates product (brand) front-loader shares.

The third moment condition is the orthogonality moment $m_3(\theta) = E\left[RER_{c(j)t}\xi_{jt}\right]$, which is based on the exclusion restriction of the price IV described in Section 5.

**3. Instrumental variable exclusion restriction:** The orthogonality condition using the real exchange rate as a price instrument:

$$m_3(\theta) = E\left[RER_{c(j)t}\xi_{jt}\right].$$

Stacking these moment conditions, I estimate $\theta_2$ using the method of simulated moments (MSM):

$$\hat{\theta}_{2,MSM} = \arg\min_{\theta_2} \hat{m}(\theta_2)'\hat{m}(\theta_2). \tag{23}$$

After obtaining nonlinear parameters and mean utilities, I estimate the linear parameters $\beta$ from:

$$\hat{\delta}_j + exp(\hat{\alpha} + \hat{\kappa}_\alpha \iota_i) p_j = x_j \beta + \xi_j, \tag{24}$$

assuming independence between observed nonprice product characteristics and unobserved quality $\xi_j$.

#### IV.B.1 Market size and share of the outside good

To estimate total market size, I assume that every seventh household considers purchasing a washer each year. According to Consumer Reports, the average life expectancy of a washer was ten years in 2009. Many households consider replacements before the end of a washer's life expectancy to benefit from new features. Some households consider purchases over multiple years, while those who recently purchased are unlikely to buy again soon. Therefore, a plausible range for annual market size is between one-fifth and one-tenth of all households. My results are robust to this assumption.

To translate estimates into total profits, consumer welfare, and fixed cost bounds in dollar terms, I scale the estimates by the annual market size for washers in the United States. Two alternative estimation methods yield similar results around the merger period. First, assuming one-seventh of total U.S. households are potential buyers each year; second, dividing annual total washer shipments reported by Appliance Portrait by the inside good's market share. Both approaches indicate a total U.S. market size of approximately 15 million households.

### IV.C Speeding up the computation of expected profits

The estimation of fixed costs and the heuristic entry algorithm both require computing expected profits across numerous product portfolios. Since this step is repeated frequently, computational efficiency is critical. Here, I briefly outline key optimizations implemented to accelerate computations.

**Computing equilibrium prices.** Each draw of second-stage marginal cost and demand shocks $e_{jt}$ requires recalculating equilibrium prices for all active products. Given that I approximate expected profits for each product portfolio using 500 draws, equilibrium prices must also be recomputed 500 times per portfolio. Efficient computation of these equilibrium prices is thus essential. Moreover, not all numerical methods for recalculating equilibrium prices reliably converge. Morrow and Skerlos (2011) evaluate several numerical methods for solving Nash–Bertrand equilibrium prices. They find that Newton methods are reliable but computationally slow, whereas fixed-point iteration using the standard BLP markup equation can be slow and sometimes fail to converge. Instead, they propose an alternative markup formulation—the $\zeta$-markup equation—which is both fast and reliable. I therefore use fixed-point iteration based on the $\zeta$-markup equation to compute equilibrium prices.

**Drawing $e_{jt}$.** The heuristic portfolio choice algorithm repeatedly compares expected profits across product portfolios differing by at most a single product. Consequently, it revisits the same portfolios multiple times. A crucial efficiency gain arises from using the same set of $e_{jt}$ draws for each product across different portfolio evaluations. Economically, this assumption is justified since firms' expectations about demand and cost shocks for a given product should not vary depending on the presence of other products. Computationally, this allows storing the expected profit estimates for each portfolio. When the algorithm revisits a portfolio, it reuses previously computed expected profits, thus eliminating redundant calculations of equilibrium prices and expected profits.

# V Appendix to Section 6: Further Parameter Estimates

## V.A Demand estimation

**Table A.4:** Detailed estimates of linear demand parameters

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | First stage | Logit OLS | Logit IV | Mixed logit |
| *Dependent variable:* | Price | $\hat{\delta}_{jt}$ | $\hat{\delta}_{jt}$ | $\hat{\delta}_{jt}$ |
| Real exchange rate | 2.033*** | | | |
| | (0.365) | | | |
| Price ('00 2012 $) | | -0.164** | -0.351** | |
| | | (0.062) | (0.178) | |
| Front-loader | 0.195 | 0.358 | 0.343 | -0.730*** |
| | (0.208) | (0.244) | (0.219) | (0.104) |
| Korean | -0.584*** | 1.569*** | 1.528*** | 1.522*** |
| front-loader | (0.187) | (0.349) | (0.345) | (0.210) |
| Fisher & Paykel | Paykel | -4.536*** | -1.455*** | -2.705** |
| front-loader | (0.322) | (0.480) | (0.796) | (1.060) |
| European high-end | 0.089 | 1.192*** | 1.246* | 1.261 |

*continued*

**Table A.4:** Detailed estimates of linear demand parameters

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | First stage | Logit OLS | Logit IV | Mixed logit |
| *Dependent variable:* | Price | $\hat{\delta}_{jt}$ | $\hat{\delta}_{jt}$ | $\hat{\delta}_{jt}$ |
| front-loader | (1.268) | (0.438) | (0.640) | (0.892) |
| Agitator | -2.513*** | 0.540** | 0.071 | -0.135 |
| | (0.276) | (0.252) | (0.481) | (0.088) |
| Stacked pair | 0.490* | -0.147 | -0.053 | -0.028 |
| | (0.279) | (0.149) | (0.183) | (0.158) |
| Stainless steel exterior | 0.471 | 0.009 | 0.112 | 0.116 |
| | (0.602) | (0.270) | (0.330) | (0.265) |
| White exterior | -0.285 | 0.624*** | 0.574*** | 0.541*** |
| | (0.360) | (0.101) | (0.122) | (0.148) |
| Energy Star | 0.019 | 0.092 | 0.097 | 0.115 |
| | (0.182) | (0.126) | (0.133) | (0.129) |
| Extra noise insulation | 0.397* | 0.312** | 0.387** | 0.418*** |
| | (0.207) | (0.120) | (0.153) | (0.101) |
| Number of special programs | 0.008 | 0.052 | 0.054 | 0.051 |
| | (0.058) | (0.039) | (0.045) | (0.033) |
| Child lockout | -0.075 | 0.200 | 0.181 | 0.185 |
| | (0.163) | (0.167) | (0.169) | (0.122) |
| Repair rate | -2.384 | 1.627 | 1.200 | 1.091 |
| | (3.151) | (2.957) | (2.778) | (1.799) |
| Total advertising expenditure | -0.006 | 0.003 | 0.002 | 0.001 |
| | (0.005) | (0.002) | (0.002) | (0.005) |
| Retailer Best Buy | -0.098 | -1.062*** | -1.080*** | -1.088*** |
| | (0.085) | (0.307) | (0.306) | (0.094) |
| Retailer H.H. Gregg | -0.368*** | -1.963*** | -2.032*** | -2.060*** |
| | (0.120) | (0.299) | (0.278) | (0.099) |
| Retailer Home Depot | -0.161 | -0.765** | -0.795** | -0.806*** |
| | (0.106) | (0.321) | (0.320) | (0.096) |
| Retailer Lowe's | -0.179** | -0.334 | -0.365 | -0.381*** |
| | (0.090) | (0.231) | (0.223) | (0.086) |

*continued*

**Table A.4:** Detailed estimates of linear demand parameters

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | First stage | Logit OLS | Logit IV | Mixed logit |
| *Dependent variable:* | Price | $\hat{\delta}_{jt}$ | $\hat{\delta}_{jt}$ | $\hat{\delta}_{jt}$ |
| Retailer Sears | 0.014 | -0.435 | -0.431 | -0.429*** |
| | (0.114) | (0.445) | (0.442) | (0.101) |
| Brand FE | *Yes* | *Yes* | *Yes* | *Yes* |
| Brand time trends | *Yes* | *Yes* | *Yes* | *Yes* |
| Year FE | *Yes* | *Yes* | *Yes* | *Yes* |
| Observations | 1,590 | 1,586 | 1,590 | 1,590 |
| Kleibergen–Paap F-statistic | 31.041 | | | |
| Own-price elasticity | | -0.964 | -2.058 | -2.542 |

*Notes:* Column (1) reports the first-stage regression results of prices on the real exchange rate. Column (2) presents estimates from the simple logit model without instrumentation. Column (3) shows estimates from the simple logit using the RER as an instrument for price. Column (4) displays results from the mixed logit model described in Section 4. Standard errors are clustered at the brand level. Own-price elasticities of residual demand are computed at the product level and averaged across products, weighting by sales volume. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

# VI Appendix to Section 7: Details on Welfare Effects

## VI.A Technical details on the portfolio choice algorithm

After initializing the algorithm, product portfolios are optimized in two loops to identify a one-step equilibrium. In the *inner loop*, a player computes the expected change in firm-level profits from adding each inactive product individually and removing each active product individually.[49] If there is a profitable one-step deviation, the player updates the product portfolio accordingly and repeats this until no profitable one-step deviations remain. In the *outer loop*, I sequentially repeat this process for each player.

In practice, the computational burden is reduced by optimizing portfolios at the brand, rather than firm, level. This requires checking fewer potential deviations per portfolio adjustment. Although I fully take into account how a portfolio adjustment impacts the firm's

[49] As realized demand and supply shocks are unobservable for potential products, I estimate expected profits based on 500 demand and supply residual draws per product.

expected profit (and not just that of the brand), a potential drawback is that for products from two brands of the same firm that are close substitutes, the entry order could affect the portfolio choice. However, firms typically segment products by brand, such that products within a brand are closer substitutes, making such cases unlikely.

To further reduce computational burden, I consider only one-step deviations, ignoring multistep deviations. Evaluating multistep deviations would be computationally infeasible in this context.[50] Given that washing machines are generally substitutes, adding multiple products simultaneously is unlikely to be profitable if adding each individually is not. However, profitable multistep deviations involving simultaneous additions and removals could exist, but checking these exhaustively is impractical. Furthermore, it may not be desirable to consider multistep deviations with many different portfolio adjustments simultaneously, since making complex portfolio adjustments is also more difficult for firms in practice.

Finally, because fixed costs are only partially identified, I implement the portfolio choice algorithm repeatedly using 50 fixed-cost draws. While the estimation of fixed-cost bounds places no restrictions on the distribution within brands, evaluating counterfactuals requires an explicit assumption. In the spirit of Wollmann (2018), I set the mean fixed cost for each brand at the midpoint of its 95-percent confidence bounds and draw the idiosyncratic product- and market-specific fixed-cost shocks, $\upsilon_{jt}$, from a normal distribution with mean zero and a standard deviation equal to 25 percent of the width of these bounds. In all counterfactuals, I report 95-percent confidence sets for welfare effects across fixed-cost draws.

## VI.B Additional results

Table A.5 repeats the analysis from Table 8, but without constraining the shipping cost parameter to the point estimate from the main sample in bootstrapped samples. As expected, this results in wider confidence intervals in Column (2). The results in Column (4) remain unaffected, as the endogenous product portfolio algorithm is estimated using only the main sample.

Table A.6 presents results from the various merger simulations comparing Whirlpool's acquisition of Maytag to a scenario with a standalone Maytag. This table extends the analysis in Table 7 by additionally accounting for scenarios that include offshoring efficiencies.

Table A.7 shows the results for the different merger simulations when comparing an acquisition of Maytag by Haier to a standalone Maytag. As expected, without cost changes, the product market implications of these two scenarios are the same. With offshoring cost

[50] For example, brands can have up to 15 potential products, implying $2^{15} = 32,768$ candidate deviations per brand iteration.

**Table A.5:** Simulated effects of Maytag acquisitions by Whirlpool vs. Haier (bootstrapping shipping cost parameter)

| | **Pre-acquisition product portfolios** | | **Endogenous product portfolios** | |
|---|---|---|---|---|
| *Cost adjustments:* | None | Offshoring | None | Offshoring |
| *Cost pass-through* | | | | |
| Whirlpool relocation | –<br>– | 86%<br>[-75%, 247%] | –<br>– | 85%<br>[84%, 87%] |
| Haier relocation | –<br>– | 85%<br>[68%, 103%] | –<br>– | 84%<br>[83%, 85%] |
| *Prices and consumer welfare* | | | | |
| Average price | 3.2%<br>[1.9%, 4.5%] | 4.6%<br>[-0.5%, 9.7%] | 4.1%<br>[3.5%, 4.7%] | 5.5%<br>[4.7%, 6.2%] |
| Consumer welfare | $-166M<br>[$-213M, $-119M] | $-215M<br>[$-380M, $-49M] | $-222M<br>[$-264M, $-179M] | $-271M<br>[$-316M, $-225M] |
| *Employment* | | | | |
| Domestic jobs maintained | 566<br>[400, 733] | 571<br>[387, 755] | 754<br>[559, 949] | 797<br>[612, 982] |
| *Industry profits* | | | | |
| Variable profits | $81M<br>[$58M, $104M] | $55M<br>[$-53M, $163M] | $79M<br>[$54M, $105M] | $47M<br>[$19M, $74M] |
| Total profits | $81M<br>[$58M, $104M] | $55M<br>[$-53M, $163M] | $106M<br>[$80M, $132M] | $83M<br>[$56M, $111M] |
| *Maytag + Whirlpool profits* | | | | |
| Maytag cost change | –<br>– | 5.9%<br>[-17.9%, 29.7%] | –<br>– | 4.7%<br>[3.9%, 5.5%] |
| Variable profits | $23M<br>[$5M, $41M] | $-16M<br>[$-168M, $136M] | $4M<br>[$-37M, $44M] | $-38M<br>[$-81M, $6M] |
| Total profits | $23M<br>[$5M, $41M] | $-16M<br>[$-168M, $136M] | $40M<br>[$24M, $57M] | $11M<br>[$-5M, $26M] |
| *Value per job required to offset consumer welfare loss* | | | | |
| Consumer welfare only | $293k<br>[$209k, $377k] | $376k<br>[$93k, $660k] | $299k<br>[$203k, $396k] | $344k<br>[$250k, $438k] |
| Consumer welfare + total industry profits | $150k<br>[$90k, $211k] | $280k<br>[$201k, $761k] | $157k<br>[$100k, $213k] | $238k<br>[$172k, $304k] |

*Notes:* The first two columns compare the effect of Maytag acquisitions by Whirlpool vs. Haier without product portfolio adjustments. The final two columns account for endogenous portfolio adjustments. Columns (1) and (3) do not allow for acquisition-related cost changes. Columns (2) and (4) account for labor and shipping cost changes due to offshoring. Ninety-five percent confidence intervals for the first two columns are computed from 200 residual bootstrap draws. Confidence sets for final two columns are based on 50 fixed cost draws for each potential product.

**Table A.6:** Simulated effects of Maytag acquisitions by Whirlpool vs. no acquirer

| | **Pre-acquisition product portfolios** | | **Endogenous product portfolios** | |
|---|---|---|---|---|
| *Cost adjustments:* | None | Offshoring | None | Offshoring |
| *Cost pass-through* | | | | |
| Whirlpool relocation | – | 86% | – | 85% |
| | – | [76%, 96%] | – | [84%, 87%] |
| Haier relocation | – | – | – | – |
| | – | – | – | – |
| *Prices and consumer welfare* | | | | |
| Average price | 3.2% | 3.2% | 4.1% | 3.6% |
| | [1.9%, 4.6%] | [1.8%, 4.6%] | [3.5%, 4.7%] | [3.0%, 4.2%] |
| Consumer welfare | $-167M | $-156M | $-224M | $-175M |
| | [$-215M, $-119M] | [$-207M, $-106M] | [$-267M, $-182M] | [$-218M, $-131M] |
| *Employment* | | | | |
| Domestic jobs maintained | -735 | -759 | -1009 | -951 |
| | [-869, -601] | [-900, -618] | [-1188, -829] | [-1120, -781] |
| *Industry profits* | | | | |
| Variable profits | $82M | $90M | $81M | $105M |
| | [$58M, $105M] | [$57M, $123M] | [$55M, $106M] | [$79M, $131M] |
| Total profits | $82M | $90M | $107M | $132M |
| | [$58M, $105M] | [$57M, $123M] | [$81M, $133M] | [$107M, $157M] |
| *Maytag + Whirlpool profits* | | | | |
| Maytag cost change | – | -3.9% | – | -7.0% |
| | – | [-7.4%, -0.3%] | – | [-7.6%, -6.4%] |
| Variable profits | $23M | $42M | $4M | $53M |
| | [$5M, $41M] | [$8M, $76M] | [$-36M, $45M] | [$11M, $95M] |
| Total profits | $23M | $42M | $41M | $90M |
| | [$5M, $41M] | [$8M, $76M] | [$24M, $58M] | [$74M, $106M] |
| *Value per job required to offset consumer welfare loss* | | | | |
| Consumer welfare only | – | – | – | – |
| | – | – | – | – |
| Consumer welfare + total industry profits | – | – | – | – |
| | – | – | – | – |

*Notes:* The first two columns compare the effect of a Maytag acquisition by Whirlpool vs. the outcomes in the absence of an acquisition. The final two columns account for endogenous portfolio adjustments. Columns (1) and (3) do not allow for acquisition-related cost changes. Columns (2) and (4) account for labor and shipping cost changes due to offshoring. Ninety-five percent confidence intervals for the first two columns are computed from 200 residual bootstrap draws. Confidence sets for final two columns are based on 50 fixed cost draws for each potential product.

changes, U.S. consumers benefit from an acquisition of Maytag by Haier, whereas U.S. workers lose out.

Table A.8 repeats the analysis in Table 8 drawing fixed cost from a distribution around the $25^{th}$ percentile of the distance between the lower- and upper-bound brand-level fixed costs, instead of its midpoint. The results are similar to the baseline results. All of the point estimates are within the confidence sets of the main estimation results in Table 8.

Table A.9 repeats the analysis in Table 8 drawing fixed cost from a distribution around the $75^{th}$ percentile of the distance between the lower- and upper-bound brand-level fixed costs, instead of its midpoint. The results are similar to the baseline results. All of the point estimates are within the confidence sets of the main estimation results in Table 8.

**Table A.7:** Simulated effects of Maytag acquisitions by Haier vs. no acquirer

| | **Pre-acquisition product portfolios** | | **Endogenous product portfolios** | |
|---|---|---|---|---|
| *Cost adjustments:* | None | Offshoring | None | Offshoring |
| *Cost pass-through* | | | | |
| Whirlpool relocation | –<br>– | 85%<br>[72%, 98%] | –<br>– | 84%<br>[83%, 85%] |
| Haier relocation | –<br>– | –<br>– | –<br>– | –<br>– |
| *Prices and consumer welfare* | | | | |
| Average price | 0.0%<br>[-0.1%, 0.1%] | -1.4%<br>[-3.5%, 0.7%] | 0.1%<br>[0.1%, 0.1%] | -1.8%<br>[-2.2%, -1.3%] |
| Consumer welfare | $-1M<br>[$-3M, $1M] | $58M<br>[$-17M, $133M] | $-3M<br>[$-3M, $-2M] | $96M<br>[$73M, $120M] |
| *Employment* | | | | |
| Domestic jobs maintained | -1302<br>[-1579, -1025] | -1330<br>[-1609, -1050] | -1763<br>[-1869, -1657] | -1748<br>[-1879, -1617] |
| *Industry profits* | | | | |
| Variable profits | $1M<br>[$-1M, $2M] | $35M<br>[$-15M, $86M] | $2M<br>[$1M, $2M] | $58M<br>[$45M, $72M] |
| Total profits | $1M<br>[$-1M, $2M] | $35M<br>[$-15M, $86M] | $2M<br>[$1M, $2M] | $48M<br>[$35M, $62M] |
| *Maytag + Whirlpool profits* | | | | |
| Maytag cost change | –<br>– | -9.7%<br>[-21.9%, 2.4%] | –<br>– | -11.7%<br>[-12.1%, -11.3%] |
| Variable profits | $0M<br>[$-1M, $1M] | $74M<br>[$-12M, $159M] | $1M<br>[$0M, $1M] | $110M<br>[$83M, $137M] |
| Total profits | $0M<br>[$-1M, $1M] | $74M<br>[$-12M, $159M] | $1M<br>[$0M, $1M] | $98M<br>[$90M, $105M] |
| *Value per job required to offset consumer welfare loss* | | | | |
| Consumer welfare only | –<br>– | –<br>– | –<br>– | –<br>– |
| Consumer welfare +<br>total industry profits | –<br>– | –<br>– | –<br>– | –<br>– |

*Notes:* The first two columns compare the effect of a Haier acquisition by Whirlpool vs. the outcomes in the absence of an acquisition. The final two columns account for endogenous portfolio adjustments. Columns (1) and (3) do not allow for acquisition-related cost changes. Columns (2) and (4) account for labor and shipping cost changes due to offshoring. Ninety-five percent confidence intervals for the first two columns are computed from 200 residual bootstrap draws. Confidence sets for final two columns are based on 50 fixed cost draws for each potential product.

**Table A.8:** Simulated effects of Maytag acquisitions by Whirlpool vs. Haier, fixed cost draws around $25^{th}$ percentile

| | **Pre-acquisition product portfolios** | | **Endogenous product portfolios** | |
|---|---|---|---|---|
| *Cost adjustments:* | None | Offshoring | None | Offshoring |
| *Cost pass-through* | | | | |
| Whirlpool relocation | – | 86% | – | 86% |
| | – | [76%, 96%] | – | [86%, 87%] |
| Haier relocation | – | 85% | – | 84% |
| | – | [72%, 98%] | – | [84%, 84%] |
| *Prices and consumer welfare* | | | | |
| Average price | 3.2% | 4.6% | 4.6% | 6.1% |
| | [1.9%, 4.5%] | [2.0%, 7.3%] | [4.0%, 5.1%] | [5.4%, 6.7%] |
| Consumer welfare | $-166M | $-215M | $-243M | $-288M |
| | [$-213M, $-119M] | [$-296M, $-133M] | [$-267M, $-218M] | [$-314M, $-262M] |
| *Employment* | | | | |
| Domestic jobs maintained | 566 | 571 | 679 | 720 |
| | [400, 733] | [407, 734] | [520, 839] | [575, 865] |
| *Industry profits* | | | | |
| Variable profits | $81M | $55M | $102M | $71M |
| | [$58M, $104M] | [$2M, $107M] | [$85M, $118M] | [$54M, $89M] |
| Total profits | $81M | $55M | $118M | $91M |
| | [$58M, $104M] | [$2M, $107M] | [$104M, $132M] | [$77M, $104M] |
| *Maytag + Whirlpool profits* | | | | |
| Maytag cost change | – | 5.9% | – | 5.3% |
| | – | [-4.3%, 16.0%] | – | [4.9%, 5.8%] |
| Variable profits | $23M | $-16M | $26M | $-12M |
| | [$5M, $41M] | [$-82M, $51M] | [$0M, $51M] | [$-39M, $15M] |
| Total profits | $23M | $-16M | $46M | $12M |
| | [$5M, $41M] | [$-82M, $51M] | [$38M, $54M] | [$4M, $20M] |
| *Value per job required to offset consumer welfare loss* | | | | |
| Consumer welfare only | $293k | $376k | $362k | $404k |
| | [$209k, $377k] | [$229k, $524k] | [$265k, $460k] | [$317k, $490k] |
| Consumer welfare + total industry profits | $150k | $280k | $186k | $277k |
| | [$90k, $211k] | [$59k, $502k] | [$133k, $239k] | [$217k, $337k] |

*Notes:* The first two columns compare the effect of a Maytag acquisition by Whirlpool with that of one by Haier without product portfolio adjustments. The final two columns account for endogenous portfolio adjustments. Columns (1) and (3) do not allow for acquisition-related cost changes. Columns (2) and (4) account for labor and shipping cost changes due to offshoring. Ninety-five percent confidence intervals for the first two columns are computed from 200 residual bootstrap draws. Confidence sets for final two columns are based on 50 fixed cost draws for each potential product.

**Table A.9:** Simulated effects of Maytag acquisitions by Whirlpool vs. Haier, fixed cost draws around $75^{th}$ percentile

| | **Pre-acquisition product portfolios** | | **Endogenous product portfolios** | |
|---|---|---|---|---|
| *Cost adjustments:* | None | Offshoring | None | Offshoring |
| *Cost pass-through* | | | | |
| Whirlpool relocation | – <br> – | 86% <br> [76%, 96%] | – <br> – | 85% <br> [83%, 87%] |
| Haier relocation | – <br> – | 85% <br> [72%, 98%] | – <br> – | 84% <br> [83%, 85%] |
| *Prices and consumer welfare* | | | | |
| Average price | 3.2% <br> [1.9%, 4.5%] | 4.6% <br> [2.0%, 7.3%] | 3.6% <br> [2.6%, 4.6%] | 4.9% <br> [3.9%, 5.9%] |
| Consumer welfare | $-166M <br> [$-213M, $-119M] | $-215M <br> [$-296M, $-133M] | $-213M <br> [$-277M, $-150M] | $-253M <br> [$-324M, $-183M] |
| *Employment* | | | | |
| Domestic jobs maintained | 566 <br> [400, 733] | 571 <br> [407, 734] | 976 <br> [666, 1287] | 1028 <br> [721, 1334] |
| *Industry profits* | | | | |
| Variable profits | $81M <br> [$58M, $104M] | $55M <br> [$2M, $107M] | $45M <br> [$-1M, $91M] | $17M <br> [$-35M, $69M] |
| Total profits | $81M <br> [$58M, $104M] | $55M <br> [$2M, $107M] | $96M <br> [$62M, $130M] | $73M <br> [$35M, $112M] |
| *Maytag + Whirlpool profits* | | | | |
| Maytag cost change | – <br> – | 5.9% <br> [-4.3%, 16.0%] | – <br> – | 4.7% <br> [3.9%, 5.5%] |
| Variable profits | $23M <br> [$5M, $41M] | $-16M <br> [$-82M, $51M] | $-36M <br> [$-109M, $38M] | $-69M <br> [$-152M, $13M] |
| Total profits | $23M <br> [$5M, $41M] | $-16M <br> [$-82M, $51M] | $34M <br> [$12M, $56M] | $8M <br> [$-15M, $31M] |
| *Value per job required to offset consumer welfare loss* | | | | |
| Consumer welfare only | $293k <br> [$209k, $377k] | $376k <br> [$229k, $524k] | $226k <br> [$111k, $340k] | $254k <br> [$131k, $376k] |
| Consumer welfare + total industry profits | $150k <br> [$90k, $211k] | $280k <br> [$59k, $502k] | $125k <br> [$52k, $198k] | $180k <br> [$97k, $263k] |

*Notes:* The first two columns compare the effect of a Maytag acquisition by Whirlpool with that of one by Haier without product portfolio adjustments. The final two columns account for endogenous portfolio adjustments. Columns (1) and (3) do not allow for acquisition-related cost changes. Columns (2) and (4) account for labor and shipping cost changes due to offshoring. Ninety-five percent confidence intervals for the first two columns are computed from 200 residual bootstrap draws. Confidence sets for final two columns are based on 50 fixed cost draws for each potential product.

# References for Online Appendix


Appliance Portrait. 2006. $29^{th}$ *Annual Portrait of the U.S. Appliance Industry.* Dana Chase.

Ashenfelter, Orley C., Daniel S. Hosken, and Matthew C. Weinberg. 2013. "The Price Effects of a Large Merger of Manufacturers: A Case Study of Maytag-Whirlpool." *American Economic Journal: Economic Policy* 5 (1): 239–61.

Berry, Steven. 1994. "Estimating Discrete-Choice Models of Product Differentiation." *The RAND Journal of Economics* 25 (2): 242–262.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica* 63 (4): 841–890.

———. 2004. "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market." *Journal of Political Economy* 112 (1): 68–105.

Brunner, Daniel, Florian Heiss, André Romahn, and Constantin Weiser. 2020. "Reliable Estimation of Random Coefficient Logit Demand Models." *mimeo.*

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

Electrolux. 2007. *Annual Report 2006.* https://www.electroluxgroup.com/en/annual-reports-27641/?decade=2000-2009.

Ferencikova, Sonia. 2002. "Transition at Whirlpool–Tatramat: From joint venture to acquisition." *Transnational Corporations* 1 (1): 69–98.

Flaaen, Aaron, Ali Hortaçsu, and Felix Tintelnot. 2020. "The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines." *American Economic Review* 110 (7): 2103–27.

Loecker, Jan De, and Paul T. Scott. 2024. "Markup Estimation using Production and Demand Data: An Application to the US Brewing Industry." *Review of Economic Studies.*

Maytag. 2005. *2004 Annual Report.* Newton, IA: Author.

McCabe, Liam. 2016. "Should You Get a Front-Load or Top-Load Washing Machine?" *New York Times,* https://www.nytimes.com/wirecutter/blog/should-you-get-a-front-or-top-load-washing-machine/.

Morrow, W. Ross, and Steven J. Skerlos. 2011. "Fixed-Point Approaches to Computing Bertrand-Nash Equilibrium Prices Under Mixed-Logit Demand." *Operations Research* 59 (2): 328–345.

Owen, Art B. 2017. *A randomized Halton algorithm in R.*

Reynaerts, Jo, R Varadha, and JC Nash. 2012. "Enhancing the Convergence Properties of the BLP (1995) Contraction Mapping." *KU Leuven Working Papers of VIVES - Research Centre for Regional Economics 482522.*

Rubens, Arthur, Sonia Ferencikova, and Roland Bardy. 2019. “How to transcend from a local subsidiary into the global leadership position of your industry: the case of Whirlpool Slovakia.” *Transnational Corporations Review* 2 (11): 120–132.

Wollmann, Thomas G. 2018. “Trucks without Bailouts: Equilibrium Product Characteristics for Commercial Vehicles.” *American Economic Review* 108 (6): 1364–1406.