UniCredit Foundation

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

**Felix Montag**

8th Econ Job Market Best Paper Award

Working Paper Series

n. 164 ■ December 2021

## Statement of Purpose

The Working Paper series of the UniCredit Foundation is designed to disseminate and to provide a platform for discussion of either work of the UniCredit economists and researchers or outside contributors (such as the UniCredit Foundation scholars and fellows) on topics which are of special interest to the UniCredit Group. To ensure the high quality of their content, the contributions are subjected to an international refereeing process conducted by the Scientific Committee members of the Foundation.

The opinions are strictly those of the authors and do in no way commit the Foundation and UniCredit.



These Working Papers often represent preliminary work. Citation and use of such a paper should take account of its provisional character.



The Working Papers are also available on our website (http://www.unicreditfoundation.org )

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

## Job Market Paper

Felix Montag*

This version: November 8, 2021
Download latest version here

**Abstract**

Proponents of industrial policy argue that merger control should consider domestic employment. I propose a model to assess how a product market merger affects rival product entry, consumer welfare, and domestic employment. Firms endogenously decide which products to offer. Domestic jobs depend on production locations and equilibrium quantities in the product market. I estimate the structural parameters of this model for the U.S. home appliance industry. Using the structural model, I examine the impact of Whirlpool's acquisition of Maytag and compare it to the impact of a counterfactual acquisition by a foreign buyer with no prior presence in the U.S. market. Four key findings emerge from the comparison of these two acquisitions: First, rival product entry is mostly independent of the acquirer. Second, a Whirlpool acquisition leads to the removal of more merging party products. Third, it always leads to lower consumer welfare. Fourth, a Whirlpool acquisition leads to a smaller decrease in U.S. employment. I use these results to estimate the job value necessary for domestic employment effects to offset consumer welfare losses.

*Department of Economics, Ludwig-Maximilians-University Munich. Email: felix.montag@econ.lmu.de. I am deeply grateful to my advisors Ali Yurukoglu, Monika Schnitzer, Ying Fan, and Fabian Waldinger for their patient guidance, constant encouragement and invaluable advice. I also thank Alessandra Allocca, Davide Cantoni, Antoine Ferey, Anna Gumpert, Patrick Kline, Matthias Lang, Ralph Ossa, Klaus Schmidt, Claudia Steinwender, Maryam Vaziri (discussant), Lulu Wang, and Martin Watzinger for helpful comments and discussions. I also greatly benefited from comments by seminar participants at the LMU Munich and the 2021 EDGE Jamboree. Financial support by 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. The paper won the *2021 Econ Job Market Best Paper Award* by the Unicredit Foundation and the European Economic Association.

# 1 Introduction

Foreign competition can make markets more competitive and benefit consumers (e.g. Bai and Stumpner, 2019). It can also lead to the offshoring of jobs and harm domestic workers (e.g. Autor, Dorn, and Hanson, 2013). Traditional merger control overlooks the latter and narrowly focuses on competition. Voters however may care about overall domestic welfare. This can create a disconnect between voters' preferences and the objective of merger control. Proponents of industrial policy therefore argue that domestic employment effects should be considered in merger control.[1]

In this paper, I ask how foreign entry alters the consumer welfare and domestic employment effects of a merger between domestic competitors. In this context, foreign entry includes an alternative foreign buyer, as well as post-merger product entry by foreign competitors. Using a structural model of demand and supply, I analyze how a product market merger affects rival product entry, consumer welfare, and domestic employment. To account for the effects of product entry and exit on consumers and employment, I embed a consumer demand model into an endogenous product choice model, where the demand for domestic labor depends on production locations and equilibrium quantities in the product market. I use this model to study the acquisition of Maytag by Whirlpool in the United States' market for clothes washers. I estimate the parameters of the model and simulate the consumer welfare and employment effects of two acquisitions: The observed acquisition of Maytag by Whirlpool, as well as a hypothetical acquisition by the alternative buyer at the time, Haier, which had no prior presence in the U.S. market. I provide descriptive evidence around the time of the actual merger to corroborate the predictions of the structural model.

Several findings emerge from the comparison of the two acquisitions: First, around the time of the acquisition of Maytag by Whirlpool, markups increase, but prices do not. Second, post-merger (foreign) rival product entry is mostly independent of who acquires Maytag. Third, a Whirlpool acquisition always leads to the removal of more merging party products than an acquisition by Haier. Fourth, a Whirlpool acquisition is always substantially worse for consumers. Fifth, a Whirlpool acquisition leads to less offshoring and a smaller decrease in U.S. manufacturing jobs. This effect is partially offset by a larger gain in market shares by foreign competitors after a Whirlpool acquisition. Sixth, I calculate how much each additional job maintained by the Whirlpool acquisition (relative to the acquisition by Haier) must be worth to counteract the larger decrease

[1] Many jurisdictions incorporate public interest considerations into merger control (see OECD, 2016). In Germany and South Africa, these include employment. There are no public interest considerations in merger control in the European Union and the United States.

in consumer welfare due to the Whirlpool acquisition. Comparing this to the estimated local labor market effects of new multinational jobs by Setzler and Tintelnot (2021), I cannot exclude the possibility that a Whirlpool acquisition leads to higher domestic welfare. Seventh, welfare effects are unequally distributed. Relative consumer welfare losses mildly decrease in household income. Employment effects are concentrated in a few local labor markets.

The 2006 acquisition of Maytag by Whirlpool is a landmark case in which the Department of Justice (DoJ) unconditionally cleared the merger between the two largest U.S. laundry product manufacturers. Prior to the merger, the Chinese appliance manufacturer Haier made an offer to acquire Maytag. Since Haier did not have a prior U.S. market presence, this acquisition would not have decreased competition. However, Haier planned to relocate Maytag's production to its existing manufacturing plants in China (Goodman and White, 2005).[2] Since there are no public interest exceptions in U.S. merger control, the employment effects should not play a role in the decision. Instead, the DoJ argued that competition would remain unharmed by a Whirlpool acquisition as any attempt to raise prices would lead to imports by foreign competitors. This was heavily disputed (see Baker and Shapiro, 2008a).

For the empirical analysis, I construct a comprehensive data set of the U.S. residential laundry market between 2005 and 2015. The core of the product market data comes from *TraQline*, a representative survey of approximately $600,000$ U.S. households per year. On the production side, I hand-collect product-level data on the locations of plants manufacturing for the U.S. market. These location data serve three purposes: First, they allow constructing a production cost shifter that can be used as an instrumental variable for prices in the demand estimation. Second, they allow simulating the effects of different counterfactual scenarios on the number of U.S. manufacturing jobs. Third, they enable a data-driven approach to estimating the marginal cost efficiencies from offshoring.[3]

I descriptively document several trends around the time of Whirlpool's acquisition of Maytag. First, concentration strongly increases for clothes washers and dryers. Second, after controlling for product characteristics, prices of clothes washers and dryers by the merging parties do not increase compared to freestanding ranges by other brands, where there was only a small pre-merger overlap.[4] Third, while LG and Samsung introduce new clothes washers and dryers after the merger, this is also true for freestanding ranges.

[2]Lacetera and Sydnor (2015) show that there is no inherent limitation to maintaining high-quality production after relocating production. This is consistent with frequent production relocations throughout the sample period.

[3]This is similar in spirit to Miller and Weinberg (2017), who estimate how the Miller/Coors merger produced marginal cost efficiencies through a reduction in shipping distance.

[4]Ashenfelter, Hosken, and Weinberg (2013) study the price effects of the Maytag acquisition using the same empirical design with other data. They also do not find any price increases for clothes washers, however they find price increases of 14 percent for newly introduced Whirlpool dryers. I discuss how these differences in results could be related to the different data sources in Section 2.

This suggests that product entry could be at least partially independent of the merger. Finally, I use a county-level difference-in-differences (DiD) design that shows that the closure of Maytag plants and of its headquarter (HQ) increases unemployment, decreases employment, and decreases average wages of the employed.[5]

Several questions remain: Does merger-independent entry reduce prices in the absence of the merger? Is overall entry sufficient to prevent the merging parties from increasing prices? If an acquisition by Whirlpool harmed consumers, could this harm be offset by benefits to U.S. workers? Answering these questions requires a model. As the descriptive trends for clothes washers and dryers are very similar, I will focus on washers from hereon after.

The model features manufacturers and consumers. Manufacturers choose their product portfolios and prices. Consumers make purchase decisions. The model is set up as a two-stage game. At the beginning of the game, each manufacturer is endowed with a set of potential products that it is technologically capable of producing. Each product is associated with an exogenous set of characteristics, a production location, and a marginal cost of production. In the first stage, each firm chooses which potential product to introduce into the market, at a per product fixed and sunk entry cost.[6] Next, marginal cost and demand shocks are realized. In the second stage, firms set prices and consumers make purchases. I model consumer demand using a static random coefficients discrete choice model, where the price sensitivity of consumers depends on income and some consumers have an unobserved taste for front-loading clothes washers. Finally, the number of manufacturing jobs is determined. This is linear in the quantities of the product market equilibrium.[7] Whether a job is created domestically or abroad depends on the exogenous production location for each product.

On the demand side, the estimation is in the spirit of S. Berry, Levinsohn, and Pakes (2004). Informally, the non-linear demand parameters are identified by the correlation between household income and purchase prices and the correlation between the characteristics of the first and second choice products. I construct a cost shifter based on the production location of each product and the real exchange rate (RER) between the production location and the U.S. This cost shifter is then used as an instrumental variable for price, which is exogenous to product-level demand conditions (see Goldberg and Verboven, 2001 or Grieco, Murry, and Yurukoglu, 2021). The granularity of the data

[5]This is in line with recent evidence showing that the presence of multinational firms affects the wages of workers at other firms (see Card, Cardoso, Heining, and Kline, 2018, Alfaro-Ureña, Manelici, and Vasquez, 2021, or Setzler and Tintelnot, 2021). Furthermore, Jacobson, LaLonde, and Sullivan (1993) show that workers separating from distressed firms suffer long-term earnings losses and that these depend on local labor market conditions.

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

[7]Wages are determined outside the model. They affect the demand for manufacturing workers through their effect on marginal costs and the product market equilibrium.

allows identifying rich substitution patterns and thus capture the closeness in competition between products.

On the supply side, I estimate the product-level marginal costs that rationalize the data assuming differentiated Bertrand-Nash competition (see Nevo, 2001). A growing literature is concerned with estimating bounds on the fixed costs of introducing a new product into the market using moment inequalities (see Pakes, Porter, Ho, and Ishii, 2015). Intuitively, the fixed and sunk cost of adding a product that was introduced to the market can at most be the expected variable profit of the product. Similarly, the fixed and sunk cost of adding a product that is part of the set of potential products but is not introduced to the market must be at least as high as the expected variable profit of that product. Methodologically, the estimation of fixed cost bounds is closest to Eizenberg (2014). Finally, I combine evidence on the number of clothes washers that a manufacturing worker produces per year with the hand-collected product-level plant locations to estimate how different product market equilibria affect the demand for domestic manufacturing workers.

I encounter several empirical challenges. A first challenge is to identify the set of potential products that multi-product firms can introduce.[8] Studying an unconditionally cleared merger allows me to overcome this challenge. For rivals, the incentives to introduce new products are greatest after the Whirlpool acquisition. Thus, any rival product not observed after this acquisition is unlikely to be introduced after a Haier acquisition. In contrast, for the merging parties I observe any product that was removed because of the merger in their pre-merger product portfolio.[9] Draganska, Mazzeo, and Seim (2009) and Fan and Yang (2021) exploit cross-sectional variation in market structure to estimate the set of potential products. This is infeasible in my setting, since I study product portfolio choices at the national level.[10] To make the analysis usable in merger control, where the post-merger outcome cannot be observed, I describe how data available to competition authorities (but not to researchers) pre-merger can be used to estimate the set of potential products and simplify the fixed cost estimation.

A second empirical challenge is the multiplicity of equilibria when simulating counterfactual entry. Due to the large number of products, computing all potential equilibria is computationally infeasible. Instead, I follow a literature (e.g. Lee and Pakes, 2009, Wollmann, 2018 or Fan and Yang, 2020) that uses heuristic learning algorithms to de-

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

[9] I do not observe products that the merging parties do not carry pre-merger, do not introduce post-merger, but would introduce in the absence of the merger. However, these products are probably less important for firm profits and consumer welfare, since firms chose not to introduce them post-merger.

[10] Eizenberg (2014) analyzes a market without cross-sectional variation in entry. He estimates the set of potential products based on existing product lines and technologies. This works in his context, as he studies how the removal of a frontier technology affects the presence of older products. This is not a viable strategy to study the introduction of new products.

termine equilibrium entry. Each player optimizes her portfolio sequentially, taking the choices of rivals as given. I iterate through players until there is no profitable one-step deviation. I exploit two institutional features for the entry algorithm: First, since firms do not choose product portfolios after the merger from scratch, I initialize the entry algorithm at the pre-merger equilibrium. Second, I increase the computational tractability of the entry game by assuming that firms optimize their product portfolio brand-by-brand, whilst taking into account the effects on the profits of other brands of the same firm. Since firms segment products targeting different consumer groups by brand, this additional restriction should not have a strong impact on equilibrium entry.

The key methodological innovation of this paper is to propose a model to analyze the trade-off between the effects on consumer welfare and employment of a product market merger and estimate its structural parameters. This analysis differs to the nascent literature on labor market power in merger analysis (e.g. Prager and Schmitt, 2021, Shapiro, 2019 or Marinescu and Hovenkamp, 2019). In my case, there is no overlap between the merging parties in local labor markets and thus also no change in labor market power.[11] Instead, I ask how the identity and restructuring plans of different potential acquirers and product market rivals affects U.S. employment.[12]

The empirical results shed light on the interaction between the consumer welfare and employment effects of a product market merger. Without efficiencies, an acquisition of Maytag by Whirlpool leads to a decrease in consumer welfare between 6.6 and 10.1 percent compared to a Haier acquisition. However, it also leads to the maintenance of 1,021 to 1,507 additional U.S. manufacturing jobs. Decomposing the employment effect into a relocation and a reallocation effect shows that foreign competition is a double-edged sword. The relocation of Maytag jobs after a Haier acquisition is greater than after a Whirlpool acquisition, since the latter only partially offshored Maytag's production. Although the presence of competitors reduces the post-merger harm to consumers, the reallocation of market shares to competitors producing abroad also mildly decreases the employment benefits of a Whirlpool acquisition.

The estimates show that domestic employment benefits of a Whirlpool acquisition as compared to an acquisition by Haier could plausibly offset losses to consumer welfare. Considering clothes washers only and without efficiencies, I show that an annual average job value of between $135,000 and $316,000 is necessary to offset consumer welfare losses. Using a back-of-the-envelope calculation, I find that this value is on average below $80,000 for other appliance categories. In comparison, Setzler and Tintelnot (2021) find that the total wage bill in a local labor market increases by around $113,000 per year for each additional job created by a foreign multinational firm. This does not include any

[11]Maytag and Whirlpool do not operate plants in the same local labor markets pre-merger.

[12]Wollmann (2018) estimates how output changes with and without the 2009 automobile bailout affect employment. He assumes that all products are always produced in the United States.

other benefits of employment, which further increase the value of a job. Given these estimates, I cannot reject that the domestic employment effects overturned the consumer welfare effects of a comparison between these two acquisitions. These findings relate to a literature that quantifies the trade-off between consumer welfare and employment of trade liberalization (see Jaravel and Sager, 2020) and restrictions (see Hufbauer and Lowry, 2012 or Flaaen, Hortaçsu, and Tintelnot, 2020). Among these estimates, I find the lowest job values necessary to offset consumer welfare changes.

Finally, I contribute novel evidence to how endogenous product portfolio choices change the consumer welfare effects of mergers.[13] I find that even for an actual merger that was marginally cleared because of an entry defense, endogenous portfolio adjustments increase the harm to consumers. This is because foreign entry is mostly independent of the merger, whereas the merger leads to fewer products offered by the merging parties. Existing studies mostly consider hypothetical changes in concentration and find mixed results. Fan and Yang (2020) find that endogenous product adjustments exacerbate negative consumer welfare effects, whereas Wollmann (2018) finds the opposite. Fan and Yang (2021) show that product portfolio adjustments exacerbate negative merger effects in small markets and reduce consumer harm in larger markets. Under certain conditions, Caradonna, Miller, and Sheu (2021) show that without marginal cost efficiencies product portfolio adjustments can never be profitable for the parties and also fully offset consumer harm. I find that marginal cost efficiencies also limit the strength of an entry defense, since they reduce the incentives for rivals to add new products.[14]

The remainder of the paper is structured as follows: The next section discusses the details of the case and describes the data. Section 3 presents the descriptive evidence, Section 4 outlines the industry model, Section 5 sketches the estimation strategy, Section 6 presents the results, Section 7 describes the welfare effects, Section 8 discusses simplifying estimation with proprietary data, and Section 9 concludes.

# 2 Institutional Setting and Data

## 2.1 The acquisition of Maytag by Whirlpool

Prior to its acquisition by Whirlpool, Maytag had been struggling financially for several years. Although the company had already cut costs by reducing its workforce by 20 percent, in 2004 it continued to struggle with cost pressure, a further decline in revenues

[13] A related literature (e.g., Werden and Froeb, 1998; Li, Mazur, Park, Roberts, Sweeting, and Zhang, Forthcoming; and Ciliberto, Murry, and Tamer, 2021) studies mergers and static entry for single-product firms. Garrido (2020) studies dynamic product entry decisions by multi-product firms assuming nested logit demand. Fan (2013) studies product repositioning after mergers. Several papers study the effect of mergers on entry and product variety for radio stations (e.g., S. T. Berry and Waldfogel, 2001; Sweeting, 2010; and Jeziorski, 2015).

[14] Cabral (2003) shows this theoretically for single-product firms.

and posted a net loss (Maytag, 2005). In May 2005, the management of Maytag agreed to be bought by a group of private investors for $1.13 billion (Barboza, 2005). In June 2005, the Chinese household appliance manufacturer Haier made a competing bid of $1.3 billion. One month later, Maytag's biggest manufacturing rival in the U.S. appliance market, Whirlpool, outbid Haier with an offer of $1.4 billion. A few days later, Haier withdrew its bid and in March 2006 Whirlpool acquired Maytag after an unconditional merger clearance by the Department of Justice.

Haier's bid came at a time when the Chinese government pushed its large companies to make foreign acquisitions to get access to foreign markets for its manufactured goods, particularly in the European Union and the United States.[15] Since Chinese acquirers were met with resistance, these acquisitions often targeted well-known brand names slipping into decline. This made the acquisition itself easier and also helped overcome the resistance of consumers towards Chinese brands in the product market.[16] With its weak financial performance and its strong brand portfolio, Maytag perfectly fit the bill. Haier, who previously had negligible sales in the U.S. appliance market, planned to use Maytag's brands, repair network and distribution channels, whilst offshoring production to Haier's existing plants in China (Goodman and White, 2005).

Against this backdrop, Whirlpool's bid for Maytag could be seen as fending off a foreign takeover. The main caveat, however, was that Whirlpool and Maytag were close competitors in the product market for several major appliance categories. In its investigation of the acquisition, the DoJ focused on residential clothes washers and dryers. For the manufacturing of laundry products, this was a merger from four to three, where Whirlpool and Maytag were the largest and second largest manufacturers in the U.S. market. With its Kenmore brand Sears was another large brand owner in the laundry market; they however did not manufacture any appliances themselves but purchased them from original equipment manufacturers (OEMs) instead. For instance, all clothes washers sold under the Kenmore brand in 2005 were produced by Whirlpool. The DoJ concluded that despite the high market shares of the merging parties, they would not be successful in raising prices because "LG, Samsung, and other foreign manufacturers could increase their imports into the U.S." (Department of Justice, 2006). It therefore unconditionally cleared the acquisition. Baker and Shapiro (2008a) called this decision "[...] a highly visible instance of underenforcement" and Baker and Shapiro (2008b) described 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, although entrants had thus far only achieved relatively low market shares.

[15] This was part of China's "Go Out Policy", promoting Chinese investments abroad (Goodman and White, 2005).

[16] A famous example is the 2005 acquisition of I.B.M.'s personal computer division by Lenovo.

## 2.2 The data

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

### 2.2.1 Sales, products, and households

The centerpiece of the data comes from *TraQline*. This is a data set well-known across the appliance industry and is used by major retailers and all of the major brands in the industry as a source for market insights.[17] In every quarter, a representative sample of around $150,000$ U.S. households is asked about appliance purchases. The survey is a repeated cross-section and in total around $600,000$ households are surveyed every year. The data spans the years 2005 until 2015. For each respondent, *TraQline* records the number of appliances bought, the price, a detailed set of product characteristics (e.g. the brand or whether a product is Energy Star certified), other brands that the household considered buying, the retailer at which the appliance was bought, as well as a detailed set of household demographics. The data includes information for clothes washers and dryers, as well as for freestanding ranges.

Although *TraQline* records detailed characteristic information, respondents are not asked to provide the exact model specification of the appliance they purchased. I therefore use brand, retailer and key characteristics information to aggregate appliance purchases into products. Most brand owners use different brands to cluster their product offering according to the consumers that they target.[18] Thus, the brand of a product already captures much of the variation in, otherwise unobserved, product quality. Certain key product characteristics need to be reported by all survey respondents. For clothes washers, this includes whether a clothes washer is a regular top-loader (with an agitator), a high-efficiency top-loader (without an agitator) or a front-loader. Finally, I further refine the product definition by using information on the retailer at which the product is sold. Different retailers serve different customers. If a brand and key characteristics combination (e.g. a Whirlpool high-efficiency top-loading washing machine) is sold at both, a higher-end retailer such as Sears, and a lower-end retailer such as Best Buy, these products may still slightly differ in other characteristics.[19] To capture all of these sources in

[17] 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 was the basis of the analysis by Ashenfelter, Hosken, and Weinberg (2013). To the best of my knowledge, the key difference between the data sets is that the retailer panel does not include any sales from Sears, which, at the time, was the largest U.S. retailer for household appliances and accounted for an important share of Maytag and Whirlpool sales.

[18] 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 should stand for quality and craftsmanship, Whirlpool for innovation and Maytag for reliability.

[19] For retailers, I distinguish between Best Buy, H. H. Gregg, Home Depot, Lowe's, Sears, and all others. The latter group pre-dominantly includes smaller, regional retailers. A further disaggregation

observed and unobserved characteristics variation, I define a product as a brand, retailer and key characteristics combination.

Other characteristics only need to be reported by a random subsample of respondents. This is to reduce the burden on respondents. Households that are selected to answer the more detailed characteristics questions do not have the possibility to opt-out, ruling out any selection problems. For clothes washers, these more detailed characteristics include whether it has a child lockout, the number of special programs, whether it is a stacked pair or whether it has additional noise insulation. For each product, I calculate the average value of these characteristics among the subsample of respondents.

Although household demographics allow constructing different geographic markets within the U.S., I decide to aggregate products at the national level, because product entry is determined for each major retailer at the national level. I also aggregate responses at the yearly level.

I enrich the *TraQline* product data set with two additional product characteristics: the brand repair rate and brand-level advertising expenditures.

The brand repair rates come from Consumer Reports, a nonprofit consumer organization that tests products across multiple categories and publishes a monthly magazine with test results by product category. Major appliances have long been an important product category for Consumer Reports. Between 2005 and 2015, clothes washers were featured at least once a year. Each report included an overview of brand-level repair rates. This data is based on responses to the Annual Product Reliability Survey conducted by the Consumer Reports National Research Center for more than $100,000$ clothes washers. I digitize this information to create a measure of the perceived product reliability of a brand in a particular year.

Annual information on advertising expenditures comes from Kantar AdSpender between 2005 and 2015. This is a database that includes information on the annual advertising expenditure of a brand by product and media channel. I use the total advertising expenditure of a brand across media channels to capture variation in brand reputation over time. Benkard, Yurukoglu, and Zhang (2021) use this data set to track brand ownership over time.

The *TraQline* data set only includes household demographics for respondents that purchase an appliance but not for those that do not. To identify how household income affects the sensitivity to prices in the demand estimation, I also need data on the unconditional distribution of income among the population of households (not only of those who purchased an appliance). For this, I draw a random sample of households from the IPUMS Current Population Survey (CPS). This data set includes rich demographic information for a representative household sample for every year in the analysis period.

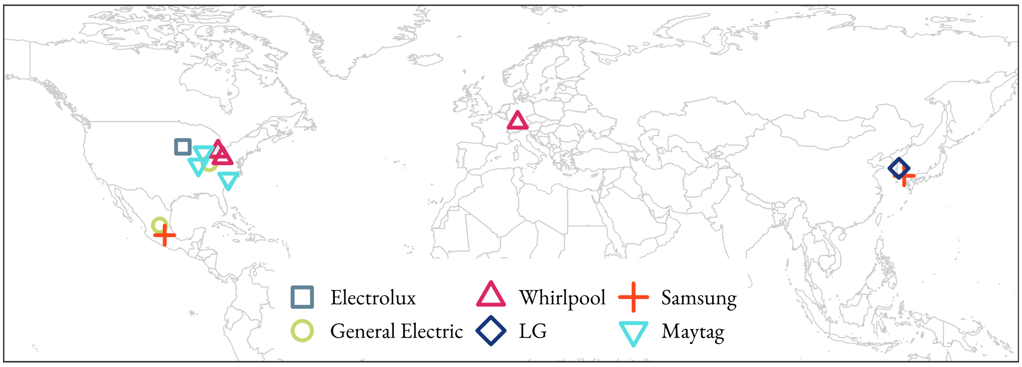
within this group would lead to many products with very few sales and thus noisy estimates.

## 2.3 Production locations and an instrumental variable for price

On the supply side, the core of the data consists of a hand-collected data set containing the locations of plants manufacturing clothes washers for the U.S. market at the product level. This data set serves three purposes. First, it allows constructing a product-level instrumental variable for prices based on differences in the production costs. Second, the product-level plant locations allow simulating how the number of U.S. clothes washer manufacturing jobs changes between counterfactual scenarios. Third, it enables a data-driven approach to estimate marginal cost efficiencies coming from offshoring and the resulting changes in production costs.

Figure 1 shows the plant locations of major clothes washer manufacturers for the U.S. market in 2005. To construct the panel of production locations, I collect production locations for all manufacturers with a market share of more than 3 percent in any year between 2005 and 2015. These are Electrolux, General Electric, LG, Maytag, Samsung, and Whirlpool. Whenever possible, I collect information on the exact plant location (e.g. Newton, Iowa). For the purpose of the analysis in this paper however, it is sufficient to know in which country a product is produced.

**Figure 1:** Clothes washer plants manufacturing for the U.S. market, 2005




Notes: The map shows all plants manufacturing clothes washers 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.5, for 2009 in Figure A.6 and for 2011 in Figure A.7.

For LG and Samsung, the production locations before 2012 are mostly based on the investigation by the U.S. International Trade Commission (USITC) into imports of large residential clothes washers from Mexico and South Korea. For 2012 until 2015, production locations for LG and Samsung are based on firm-level clothes washer imports based on the PIERS data set, which uses bill of landing documents and is reported in Flaaen, Hortaçsu, and Tintelnot (2020).

For Electrolux, Maytag and Whirlpool, the bulk of the information on manufacturing plant locations is based on information in their annual reports. Since General Electric is not primarily an appliance manufacturer, its annual report does not contain information on appliance plant locations. I therefore base plant locations on a combination of documents from the USITC investigation and news reports. Finally, to make sure that plants produce clothes washers for the U.S. market, I check plant locations against import data split by top-loading and front-loading clothes washer at the country-level from the USITC.

Occasionally, a product is produced in multiple countries for the U.S. market (e.g. in 2008 Whirlpool front-loaders are produced in Mexico and Germany). In this case, I use the same sources as described above to construct weights on the share of the product produced in each production location. I summarize plant weights in Table A.1.

To explain the need for an instrumental variable for price and how I construct one, let us briefly jump ahead to the estimation of clothes washer demand as part of the structural model. As is well-known in the literature on demand estimation, there can be unobserved demand shocks that simultaneously affect prices and quantities. Simply regressing quantities on prices would therefore lead to biased estimates. To get an unbiased estimate of the reaction of quantities to price changes, I need an instrument for price that is unrelated to unobserved demand shocks (exogeneity) and has a sufficiently strong effect on prices (relevance).

An ideal instrument is a variable that captures differences in product-level marginal costs and is unrelated to demand. I use the product-level weighted average real exchange rate (RER) between the U.S. and the countries in which the production of the product is located. This is also used by Grieco, Murry, and Yurukoglu (2021) to estimate demand for automobiles. The RER comes from the Penn World Table. Product-level plant weights are constructed as described above.

I use the RER based on consumption expenditures. This is calculated 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). It therefore consists of differences in the relative price levels and serves as a proxy for the local wage level, as well as fluctuations in the nominal exchange rate.

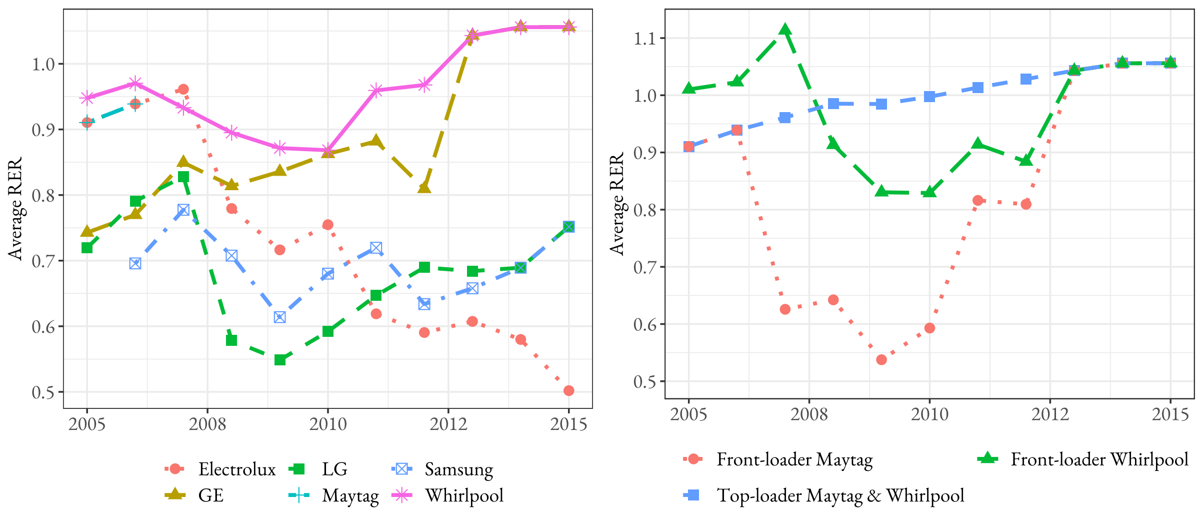
Figure 2 shows the evolution of the average RER over time and illustrates the source of the variation. The left panel plots the average RER of all production locations for a particular manufacturer. The average RER is based on the country-level RER of different plant locations of a manufacturer for a product in a particular year, weights that capture which share of a product is produced by a particular plant, and weights based on the sales volume of different products sold by a manufacturer. Although this masks within-manufacturer variation in the RER, already at this level there is significant variation. In the right panel, I further disentangle the average RER for Whirlpool and Maytag products.[20] This shows that there is additional variation in the RER below

[20]Maytag includes all products marketed under the brands owned by Maytag pre-acquisition (i.e.

the manufacturer level, because the same manufacturer produces different products in different countries. For example, whereas all Maytag and Whirlpool top-loaders are produced in the U.S., over the sample period Maytag front-loaders were produced in the U.S. and Mexico and Whirlpool front-loaders in the U.S., Mexico and Germany.

**Figure 2:** Average real exchange rate over time

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




Notes: The left panel plots the average real exchange rate of all production locations by manufacturer over time. It includes the RER for all manufacturers with a market share of at least 3 percent in any year in the sample. The right panel plots the average RER of all production locations by product of the merging parties. The average RER is based on the plant locations in a particular year, the plant weights and the country-level RER. In the right panel, Maytag includes all products marketed under the brands owned by Maytag pre-acquisition (i.e. Admiral, Amana, MagicChef and Maytag) and Whirlpool includes all other brands owned by Whirlpool.

The large variation in the RER over time is also consistent with anecdotal evidence about the importance of the local cost of production for appliance manufacturers. One of the principal reasons why Maytag was struggling financially pre-merger was that its production costs were too high, in parts due to its lack of international production.[21] In a similar spirit, Electrolux launched its global cost-cutting program in 2004, with the aim to offshore more than half of its production to low-cost countries by 2009 (Electrolux, 2007).[22] Both firms exclusively served the U.S. clothes washer market from the U.S. until 2007. This highlights the importance of production locations for costs and competitiveness in the appliance industry and also describes the source of variation in the cost measure: Changes in the RER between the U.S. and a particular production location over time, as well as changes in the production locations.

Admiral, Amana, MagicChef and Maytag) and Whirlpool includes all other brands owned by Whirlpool.

[21]This was highlighted throughout Maytag's 2004 annual report, as for example in the following: "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).

[22]By the end of the sample period, Electrolux had lost most of its share of the U.S. laundry market and served its remaining customers from low-cost countries.

## 2.4 Labor market data

Finally, I use data on local labor markets from the U.S. Bureau of Labor Statistics (BLS). To analyze the labor market effects of plant closures, I am particularly interested in local wage and employment data. These come from the Quarterly Census of Employment and Wages (QCEW) and the Local Area Unemployment Statistics (LAUS).

The QCEW collects quarterly employment and wage data at the county level as reported by employers. I use the quarterly wages per employee, disaggregated by county and industry. These wages include total compensation, bonuses, stock options, severance payments, the cash value of meals and lodging, tips, and other gratuities. I annualize these wages for ease of interpretability.

The LAUS aggregates data from state-level workforce agencies. It includes monthly information on the number of employed and unemployed individuals for every U.S. county.

# 3 Descriptive Evidence

Before diving into the theoretical model, I document descriptive trends around the Maytag acquisition. To this end, I study the evolution of concentration, prices, product entry, and U.S. appliance manufacturing employment around the time of the acquisition.

## 3.1 Changes in concentration

Table 1 shows the evolution of brand owner shares around the time of the Maytag acquisition by Whirlpool. Prior to the merger, Whirlpool and Maytag were the largest and third largest brand owners for laundry products in the U.S. market. Since Sears does not manufacture any appliances itself, Whirlpool and Maytag were also the largest and second largest laundry product manufacturers.[23] In contrast, Haier had no significant market shares in either product market.

The largest rival manufacturers of clothes washers and clothes dryers before the merger were General Electric and Electrolux. LG started gaining market shares, whereas Samsung was not yet present in the U.S. laundry market in 2005. It did, however, already have existing relationships with retailers, since it sold other products (e.g. consumer electronics) at these retailers.

[23] One approach could be to count all sales of Sears products towards the respective manufacturer. This would not be an appropriate reflection of market power, however, as Sears could switch supplier if faced with a large increase in prices. Indeed, although Whirlpool manufactured all Sears clothes washers prior to the merger, Sears switched to LG as a supplier of front-loading clothes washers in 2008. This shows that switching suppliers is not only a theoretical possibility and suggests that separately analyzing brand owners is more appropriate.

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

| | **Clothes washers** | | | **Clothes dryers** | | |
|---|---|---|---|---|---|---|
| | 2005 | 2007 | 2009 | 2005 | 2007 | 2009 |
| Whirlpool | 25 | 44 | 42 | 27 | 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 | 5 | 0 | 1 | 5 |
| HHI | 2,048 | 2,729 | 2,506 | 2,072 | 2,784 | 2,507 |
| ΔHHI | 1,149 | | | 1,124 | | |

Notes: The table shows the market share in terms of volume sales by brand owners for clothes washers and clothes dryers pre-merger (2005) and post-merger (2007 and 2009). The HHI is calculated as the sum of squared market shares using whole percentages. The increase in the HHI is based on pre-merger market shares.

The pre-merger Herfindahl-Hirschman Index (HHI) and the increase in the HHI because of the merger based on pre-merger market shares indicate that the transaction led to a strong increase in concentration.[24] According to the U.S. horizontal merger guidelines, the acquisition therefore potentially raises significant competitive concerns.[25]

Finally the evolution of market shares from just after the merger in 2007 to 2009 show that although some rivals gained market shares and the HHI gradually declined (as compared to the post-merger HHI based on pre-merger market shares), the increase in concentration due to the merger remains substantial and persistent.

## 3.2 Evolution of prices

I next turn to the descriptive evolution of prices around the time of the acquisition. Ashenfelter, Hosken, and Weinberg (2013) compare the evolution of Maytag and Whirlpool product prices for appliance categories with a large increase in concentration to categories with low increases in concentration. Since I use a different data source, I repeat the descriptive price analysis. In particular, the *NPD* data used by Ashenfelter, Hosken, and Weinberg (2013) only includes product sales at a subset of retailers (e.g. omitting sales at Sears), which could lead to systematically different results.

As a comparison appliance category, I use freestanding ranges.[26] This is an appro-

[24]The HHI is calculated as the sum of squared market shares using whole percentages (i.e. 1 to 100).

[25]The U.S. horizontal merger guidelines identify mergers with a pre-merger HHI between $1,500$ and $2,500$ and an increase in the HHI by more than 100 as potentially raising significant competitive concerns.

[26]Ashenfelter, Hosken, and Weinberg (2013) use ranges, cooktops, ovens and freezers as comparison categories.

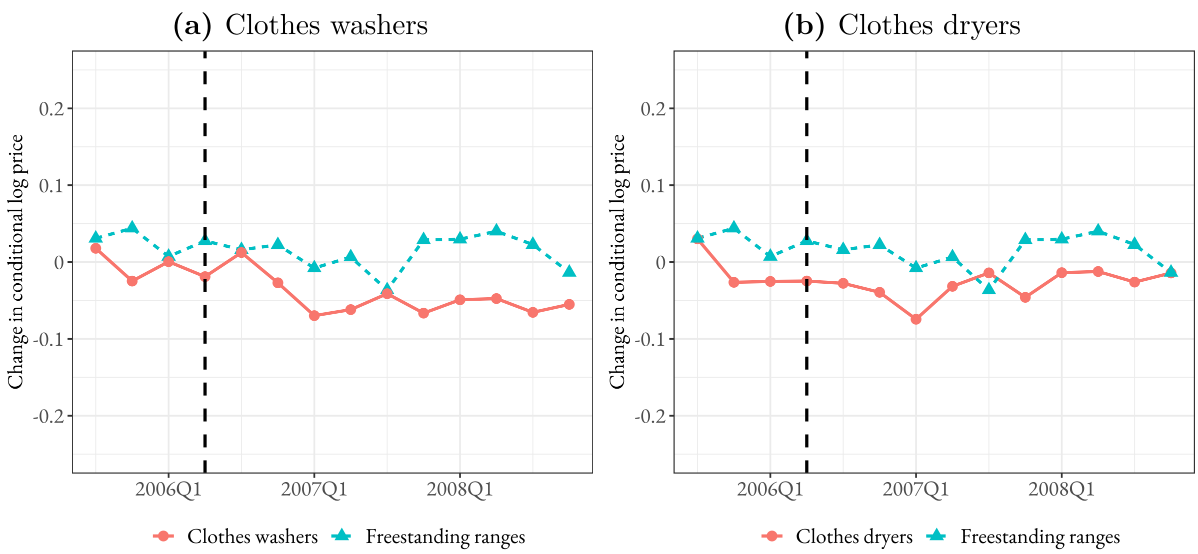
priate control group if, in the absence of the merger, prices would have evolved similarly in the treatment and the control groups. Since I cannot observe the price evolution of laundry products without the merger directly, I use two indirect ways of assessing this assumption. First, I verify the parallel trends assumption prior to the acquisition. Second, I assess whether other market trends, in particular product entry, are likely to have affected the treatment and control groups similarly, had the merger not occurred.

The analysis starts in the first quarter of 2005 and ends in the last quarter of 2008. Each observation is a product in a particular quarter. To analyze the evolution of prices conditional on product characteristics in the treatment and control groups, I estimate the parameters of the following model for each appliance category separately

$$log(p_{it}) = \beta x_{it} + \gamma_t + \epsilon_{it} \, , \tag{1}$$

where $log(p_{it})$ is the logarithm of price for product $i$ at time $t$, $x_{it}$ is a vector of product characteristics and $\gamma_t$ are quarter $\times$ year fixed effects. For clothes washers and dryers, I only include products by Whirlpool and Maytag. For freestanding ranges, I only include products not produced by Whirlpool and Maytag. Instead of product fixed effects, I control for a rich set of characteristics, including the brand and the retailer. This has the advantage of not absorbing merger-specific price changes into the fixed effects for products present only before or only after the merger.[27]

**Figure 3:** Change in the average log price conditional on product characteristics




Notes: The solid red line shows the characteristics adjusted log price of Maytag and Whirlpool clothes washers and clothes dryers. The dashed blue line shows the characteristics adjusted log price of competitor freestanding ranges. The vertical line corresponds to the date of the merger, 30 March 2006.

Figure 3 plots the quarterly fixed effects $\gamma_t$ for clothes washers and dryers over

[27] Ashenfelter, Hosken, and Weinberg (2013) show that controlling for product characteristics instead of product fixed effects yields to similar overall time trends, suggesting that there are no important additional unobserved product quality differences.

**Table 2:** Reduced form price effects of the Maytag acquisition

| | Washers vs. ranges | | | Dryers vs. ranges | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Merging parties × post | -0.030 | | | -0.017 | | |
| | [-0.076, 0.016] | | | [-0.081, 0.046] | | |
| Maytag × post | | -0.049** | -0.026 | | -0.043 | -0.015 |
| | | [-0.097, -0.001] | [-0.070, 0.018] | | [-0.097, 0.011] | [-0.063, 0.032] |
| Whirlpool × post | | -0.016 | -0.006 | | 0.007 | 0.028 |
| | | [-0.077, 0.045] | [-0.036, 0.023] | | [-0.048, 0.062] | [-0.018, 0.075] |
| 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 | 3599 | 3599 | 3280 | 4088 | 4088 | 3739 |

Notes: Columns (1) to (3) compare the logarithm of prices for clothes washers and freestanding ranges. Columns (4) to (6) compare the logarithm of prices for clothes dryers and freestanding ranges. Differences in observations in columns (3) and (6) as compared to preceding columns are due to the iterative dropping of singleton observations when clustering standard errors. 95% confidence intervals are reported in parentheses. Standard errors are clustered at the brand level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

time, as well as for freestanding ranges as a control group. The time fixed effects evolve mostly horizontally for freestanding ranges, indicating that there are no important price increases over the observation period. For clothes washers by the merging parties, these are mildly decreasing over time. For dryers, this decrease is less pronounced than for washers. Overall, the descriptive evidence suggests that there are no price increases for either clothes washers or dryers throughout the observation period.

I next estimate the price effects around the time of the merger separately for Maytag and Whirlpool products, using freestanding ranges as a control group. To do this, I estimate the parameters of the following model for washers (treatment) and freestanding ranges (control) and for dryers (treatment) and freestanding ranges (control)

$$log(p_{it}) = \alpha_1 \text{Maytag}_{it} \times \text{post}_t + \alpha_2 \text{Whirlpool}_{it} \times \text{post}_t + \beta x_{it} + \tau_i + \gamma_t + \epsilon_{it}\,. \tag{2}$$

The parameters of interest are $\alpha_1$, which captures the average price increase for Maytag products and $\alpha_2$, which captures the average price increase for Whirlpool products.

Table 2 includes the estimates of the reduced form effects of the Maytag acquisition on the logarithm of prices. Columns (1) and (4) include estimates from a regression where I pool Maytag and Whirlpool products together and estimate a joint price effect. These results suggest that there is no large price increase for clothes washers or dryers. Based on the 95% confidence intervals, I reject price increases of more than 1.6 percent for clothes washers and 4.6 percent for dryers.

In Columns (2) and (5), I disaggregate this by Maytag and Whirlpool products. Based on the 95% confidence intervals, I reject large price increases for Maytag products in both categories. For Whirlpool products, the point estimates are just below (washers) and just above (dryers) zero, however, the width of the confidence intervals do not allow me to reject price changes of between −7.7 and +4.5 percent for clothes washers and −4.8 and +6.2 percent for clothes dryers. In Columns (3) and (6) I repeat the previous analysis, however swapping brand fixed effects for more granular product fixed effects. This leads to a smaller price decrease for merging party products after the merger, but decreases are still found for Maytag clothes washers and dryers and Whirlpool washers.

A causal interpretation of these results could lead to two conclusions: First, the acquisition of Maytag by Whirlpool at most mildly increased prices for laundry products. Second, the acquisition similarly affected clothes washers and dryers.

Irrespective of whether these findings are causal, they are only partially in agreement with the findings by Ashenfelter, Hosken, and Weinberg (2013). In line with their results, I do not find any reduced form evidence for clothes washer price increases around the time of the acquisition. In contrast to their results, I also do not find any reduced form evidence for large price increases for dryers.[28] Given the very similar evolution of market shares and prices for washers and dryers, it seems plausible to expect similar price effects of the merger for both categories. Although I cannot verify this claim, as I do not have access to the *NPD* data used by Ashenfelter, Hosken, and Weinberg (2013), selection in how *NPD* recorded sales could be responsible for the different results.

In any event, the estimated price effects from the reduced form regressions should be interpreted with great caution. As previously described, a causal interpretation of these results requires that prices for laundry products would evolve similarly to prices for freestanding ranges in the absence of the merger. As also noted by Ashenfelter, Hosken, and Weinberg (2013), product entry by LG and Samsung in the market for clothes washers may confound the reduced form estimates of the price effects of the merger. These entries may or may not be related to the merger. Similar market trends may or may not be present for clothes dryers and freestanding ranges.[29]

Finally, the regression analysis does not treat products differently depending on their relative importance in the marketplace (i.e. their market share). Thus, if price changes are not homogeneous across all products, the estimated price changes may strongly be influenced by many products with relatively low market shares. If these are products that most consumers do not consider in any case, this may not be the most informative estimate to assess the price effects experienced by consumers.

[28] Compared to ranges, they find an increase in prices for Maytag dryers newly introduced after the merger of 3 percent and of 14 percent for Whirlpool dryers newly introduced after the merger. They also find that the acquisition did not change prices of old Maytag dryers and reduced prices of old Whirlpool dryers by 6 percent. Unfortunately, the data does not allow me to identify when a product was first introduced to the market and so I cannot make this additional decomposition.

[29] Using more or different appliance categories in the control group does not necessarily alleviate the problem, since it remains difficult to establish that the control markets would have developed like the treatment markets in the absence of the acquisition.

## 3.3 Product entry

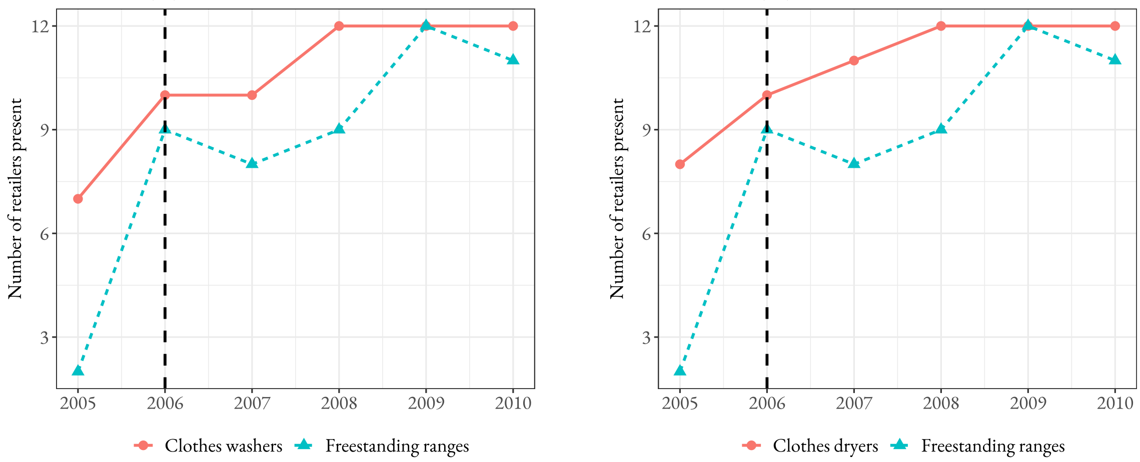
Rival product entry could affect the estimated price effects of the merger in two distinct ways: First, if the merger leads to merger-specific product entry, this can increase competition and decrease prices compared to a situation without merger-specific entry. Second, if there is merger-independent product entry by rivals into the residential laundry market around the time of the merger, this could also increase competition and reduce prices.

I therefore assess whether product entry by LG and Samsung occurred in the U.S. laundry market and whether this was different to entry patterns for freestanding ranges.

Figure 4 shows the evolution of the retailer presence by LG and Samsung for clothes washers, dryers, and freestanding ranges. Since I distinguish between five major retailers and "other retailers", the sum of retailers carrying LG and Samsung appliances can at most be twelve. Two trends emerge: First, the number of retailers carrying LG and Samsung laundry products increases around the time of the merger. By 2008, all major retailers carry LG and Samsung clothes washers and dryers. Second, there is also a strong and persistent increase in the number of retailers carrying LG and Samsung freestanding ranges. Growth is stronger, as it starts from a very low level, however full retailer coverage is only temporarily reached in 2009.

**Figure 4:** Retailer presence LG and Samsung by product category

**(a)** Clothes washers **(b)** Clothes dryers




Notes: The solid red lines show the sum of retailers that carry clothes washers (left) or dryers (right) by LG and Samsung summed together. The dashed blue line shows the sum of retailers that carry freestanding ranges by LG and Samsung.

These results suggest that product entry occurred but was not necessarily merger-specific. Indeed, if we believe that merger-independent entry for laundry products is similar to the observed product entry for freestanding ranges, we would expect to observe product entry by LG and Samsung also in the absence of the Whirlpool acquisition.

## 3.4 Labor market effects of plant closures

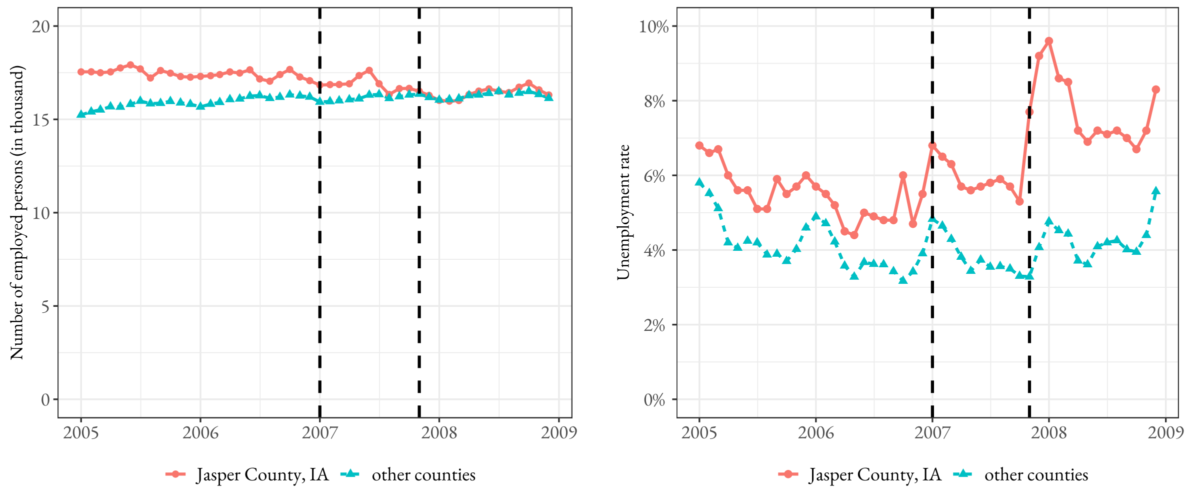
The analysis so far focused on the product market effects of the acquisition. Different acquisitions may also entail different changes to employment. For those to enter the overall welfare effects, appliance manufacturing jobs need to matter for local labor markets. In the following, I assess how Maytag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

Although Whirlpool maintained some of Maytag's manufacturing plants (e.g. in Amana, Iowa, or 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), as well as manufacturing and headquarter operations in Newton, Iowa (1,000 manufacturing and 1,800 corporate jobs). At the same time, Whirlpool announced adding 1,500 jobs at two existing plants in Ohio.

Figure 5 plots the number of employed persons and the unemployment rate in Jasper County, Iowa compared to the mean across other counties in Iowa.[30] Operations began shutting down in Jasper County on 31 December 2006, with manufacturing continuing until 31 October 2007. Already from the descriptive analysis it becomes clear that employment decreased persistently and unemployment shot up around the time of the plant closure and the shut down of corporate operations. The increase in unemployment appears to be persistent and still present at the end of 2008.

**Figure 5:** Labor market effects of the plant and HQ closures in Jasper County, Iowa

**(a)** Employment **(b)** Unemployment




Notes: The solid red lines show the evolution of the total number of employed persons and the unemployment rate in percentages in Jasper County, Iowa (county of the Maytag plant and corporate offices in Newton), respectively. The dashed blue lines show the average number of employed persons and the unemployment rate by county for all other counties in Iowa, respectively. The vertical dashed lines indicate the shut down of operations on 31 December 2006 and 31 October 2007.

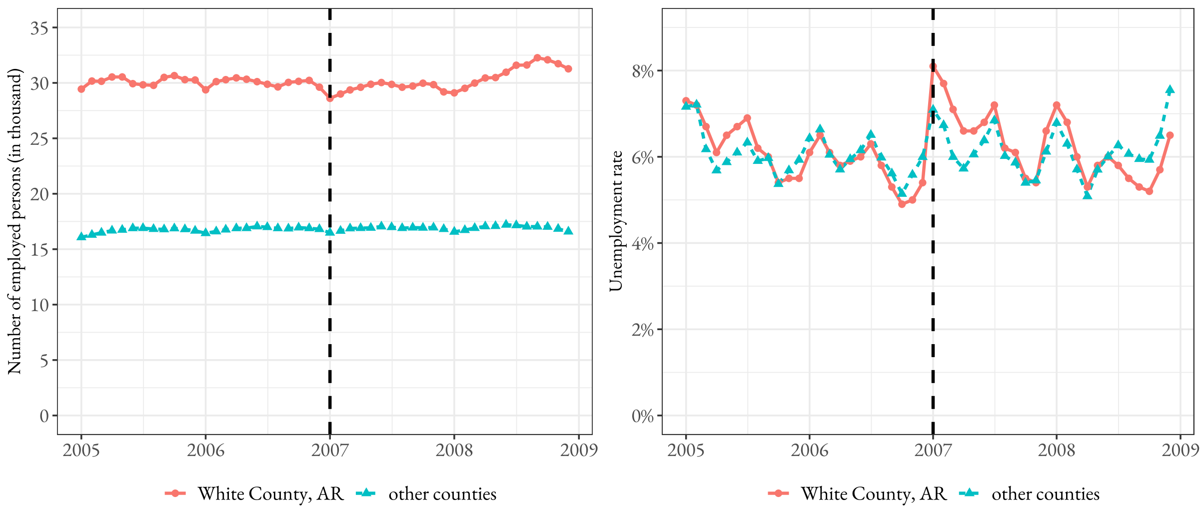
I next investigate whether this effect is also present when there are no corporate

[30] Jasper County is the county in which Newton is located.

operations and only a plant closes. Figures 6 and 7 plot the evolution of employment and unemployment in White County, Arkansas, and Williamson County, Illinois compared to other counties in Arkansas and Illinois, respectively.[31] In both counties, the Maytag appliance manufacturing plants were shut down on the 31 December 2006. In both counties, there is an increase in unemployment in the year after the plant closure. The effect appears more pronounced and persistent for Williamson County. In both counties, the difference in unemployment appears to fade away after a year.

**Figure 6:** Labor market effects of the plant closure in White County, AR

**(a)** Employment **(b)** Unemployment




Notes: The solid red lines show the evolution of the total number of employed persons and the unemployment rate in percentages in White County, Arkansas (county of the Maytag plant in Searcy), respectively. The dashed blue lines show the average number of employed persons and the unemployment rate by county for all other counties in Arkansas, respectively. The vertical dashed lines indicate the shut down of operations on 31 December 2006.

To quantitatively asses the local labor market effects of changes in Maytag employment, I estimate the parameters of the following regression model

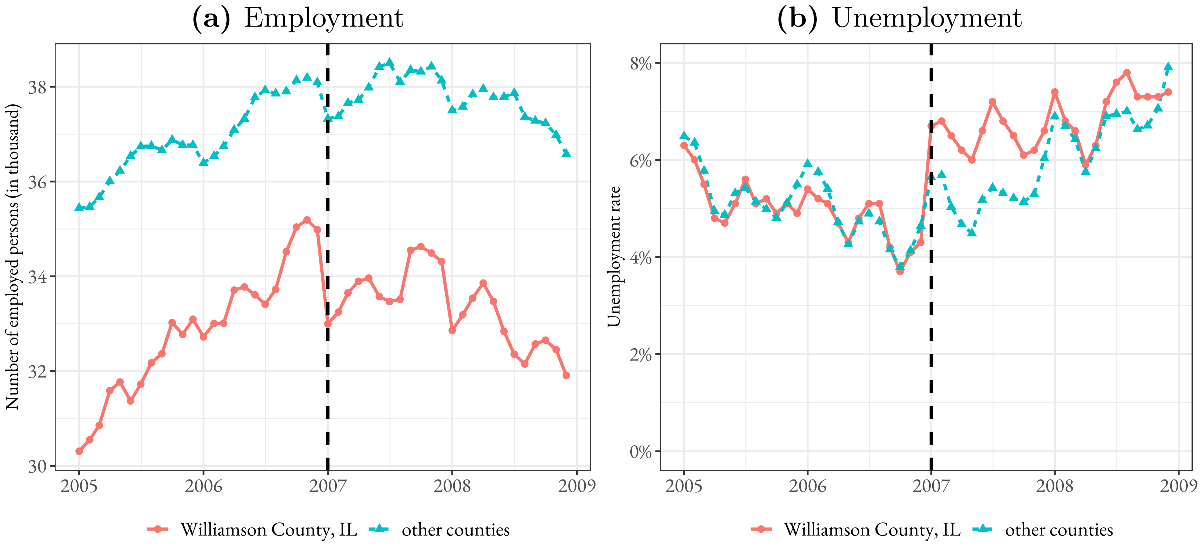
$$\text{outcome}_{it} = \alpha_1 \mathbb{1}\left(\text{year}_t = 2007\right) \times \Delta\text{jobs}_i + \alpha_2 \mathbb{1}\left(\text{year}_t = 2008\right) \times \Delta\text{jobs}_i + \tau_i + \gamma_t + \epsilon_{it}\,, \quad (3)$$

where $\text{outcome}_{it}$ is the number of employed persons, unemployed persons, or the average wage of employed persons in a particular county $i$ and time period $t$, $\Delta\text{jobs}_i$ is an indicator variable equal to one if a particular county is affected by job cuts or newly created jobs by the merging parties, $\tau_i$ are county fixed effects and $\gamma_t$ are time fixed effects.

I group counties into three different treatment groups and estimate separate regressions for each. The first treatment group is Jasper County, in which there was a shut down of manufacturing and corporate operations. The second treatment group are White County and Williamson County, in which only manufacturing plants were shut down. The

[31]White County is where Searcy is located and Williamson County is where Herrin is located. I omit Cook County (Chicago) from the control group for Illinois.

**Figure 7:** Labor market effects of the plant closure in Williamson County, IL




Notes: The solid red lines show the evolution of the total number of employed persons and the unemployment rate in percentages in Williamson County, Illinois (county of the Maytag plant in Herrin), respectively. The dashed blue lines show the average number of employed persons and the unemployment rate by county for all other counties in Illinois (with the exception of Cook County which contains Chicago), respectively. The vertical dashed lines indicate the shut down of operations on 31 December 2006.

third group is Marion County and Sandusky County, where Whirlpool created new jobs.

Table 3 summarizes the regression estimates for the elimination of jobs. Column (1) reports the effects on unemployment in Jasper County. I find that there is a statistically and economically significant increase in unemployment. The effect is persistent throughout the observation period, but is small in magnitude (around 300 persons in 2008) compared to the number of Maytag jobs lost (1,000 manufacturing and 1,800 corporate jobs). This however only tells part of the story, as it masks other shifts into non-employment, such as early retirements, exits into education, as well as out-migration. The results in Column (3) show that the number of employed persons in Jasper County as compared to before the closing of operations declined by around 1,700. Finally, Column (5) shows the effect on annualized average wages of employed persons. Again, there are large and statistically significant decreases in average wages. In Appendix Tables A.4 and A.6, I estimate wage effects separately for the manufacturing industry and all private sector jobs outside the manufacturing industry. Although wage decreases are much larger for the manufacturing industry, suggesting that many well-paying Maytag jobs were eliminated, I also find significant decrease in wages in other industries. This suggests that Maytag's presence also led to other well-paying jobs and exerted positive wage pressure on the labor market.

Columns (2) and (4) include the effects on unemployment and employment of only shutting down plants without the effects of closing the HQ. There is an economically meaningful but statistically noisy increase in unemployment. This effect however appears

**Table 3:** Reduced form labor market effects of plant and HQ closures

| | Unemployment (persons) | | Employment (persons) | | Wages ($) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Plant & HQ closure × $\mathbb{1}$ (year = 2007) | 163*** | | -1140*** | | -2472*** | |
| | [151, 176] | | [-1343,-937] | | [-2666, -2278] | |
| Plant & HQ closure × $\mathbb{1}$ (year = 2008) | 291*** | | -1716*** | | -6508*** | |
| | [263, 319] | | [-1983,-1449] | | [-6740, -6275] | |
| Plant closure × $\mathbb{1}$ (year = 2007) | | 257 | | -288* | | -329 |
| | | [-189, 704] | | [-597,21] | | [-1590, 931] |
| Plant closure × $\mathbb{1}$ (year = 2008) | | 8 | | -336** | | -400 |
| | | [-545, 561] | | [-639,-33] | | [-1815, 1014] |
| County fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,752 | 8,352 | 4,752 | 8,448 | 1,584 | 2,816 |
| Mean outcome in treated counties | 1,130 | 1,123 | 11,840 | 13,815 | 34,404 | 25,524 |

Notes: Columns (1) and (2) compare the absolute number of unemployed persons in treated counties to all other counties in the same state. Columns (3) and (4) compare the absolute number of employed persons in treated counties to all other counties in the same state. Columns (5) and (6) compare the average annualized gross wage of employed persons in treated counties to all other counties in the same state. Columns (1), (3) and (5) compare Jasper County (county of Newton) to all other counties in Iowa. Columns (2), (4) and (6) compare White County (Searcy) and Williamson County (Herrin) to all other counties in Arkansas and Illinois. Cook County (county of Chicago), is omitted from any analyses involving Illinois. 95% confidence intervals are reported in parentheses. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

to only be transitory and disappears after a year. There is a more robust and persistent decrease in employment in affected counties of around 300 persons. Since the affected plants in the two treatment counties employed 700 and $1,000$ persons respectively, this suggests that around a third to half of the jobs were permanently lost and led to out-migration or other shifts into non-employment, beyond unemployment. The results in Column (6) and in Appendix Tables A.4 and A.6 suggest that there is a significant decrease in manufacturing wages but no effect on wages in other industries.

Table 4 shows the effect of relocating $1,500$ new jobs to two existing Whirlpool plants in two different counties in Ohio. On average, this is equivalent to 750 new jobs per affected county. The results in Columns (1) and (2) suggest that these new jobs led to a significant reduction in unemployment in 2008 and an increase in employment. Additional results in Appendix Tables A.5 and A.7 show that this effect is completely driven by an increase in employment in the manufacturing industry and accompanied by a modest decrease in employment in other industries. Wages do not increase, suggesting that these new jobs do not lead to positive wage pressure on the local labor market.

**Table 4:** Reduced form labor market effects of new jobs

| | Unemployment (persons) | Employment (persons) | Wages ($) |
|---|---|---|---|
| | (1) | (2) | (3) |
| New jobs × $\mathbb{1}$ (year = 2007) | -33 | 358 | -88 |
| | [-178,112] | [-151,867] | [-412,237] |
| New jobs × $\mathbb{1}$ (year = 2008) | -230** | 656 | -271 |
| | [-458,-2] | [-169,1480] | [-1299,758] |
| County fixed effects | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes |
| Observations | 4,224 | 4,224 | 1,408 |
| Mean outcome in treated counties | 2,067 | 27,006 | 32,452 |

Notes: Column (1) compares the absolute number of unemployed persons in Marion County (Marion) and Sandusky County (Clyde) to all other counties in Ohio. Column (2) compares the absolute number of employed persons in Marion County and Sandusky County to all other counties in Ohio. Column (3) compares the average annualized gross wage of employed persons in Marion County and Sandusky County to all other counties in Marion County and Sandusky County. 95% confidence intervals are reported in parentheses. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# 4 The Model

Three observations emerge from the preceding analysis. First, entry played a crucial role in the product market and so understanding entry is necessary to assess the effects of the merger. Second, although there were many changes in the product portfolios of existing firms, there was no entry by a new firm. The focus thus lies on endogenous portfolio choices and I abstract from firm-level entry. Third, there are frictions in local labor markets and important differences in the production locations of manufacturers. Where products are produced and by whom affects the welfare effects of the merger.

The model features manufacturers and consumers. Manufacturers choose their product portfolios and prices. Consumers make purchase decisions. The model proceeds in two stages. In the first stage, firms are endowed with a set of potential products that they are technologically capable of producing and their production locations. They observe product-level shocks to entry costs and decide which products to offer. At this stage, firms do not observe transitory demand and marginal cost shocks and only form expectations about these shocks. In the second stage, demand and marginal cost shocks realize and are observed by firms, upon which they set prices. Finally, households observe the products on offer and their characteristics, including prices, and make their purchase decisions. The number of domestic production jobs depends on equilibrium quantities in the product market and the location of production.

I solve this game backwards by searching for the Subgame Perfect Nash Equilibria (SPNE) of the game.[32] To estimate the parameters of the game, I require the existence

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

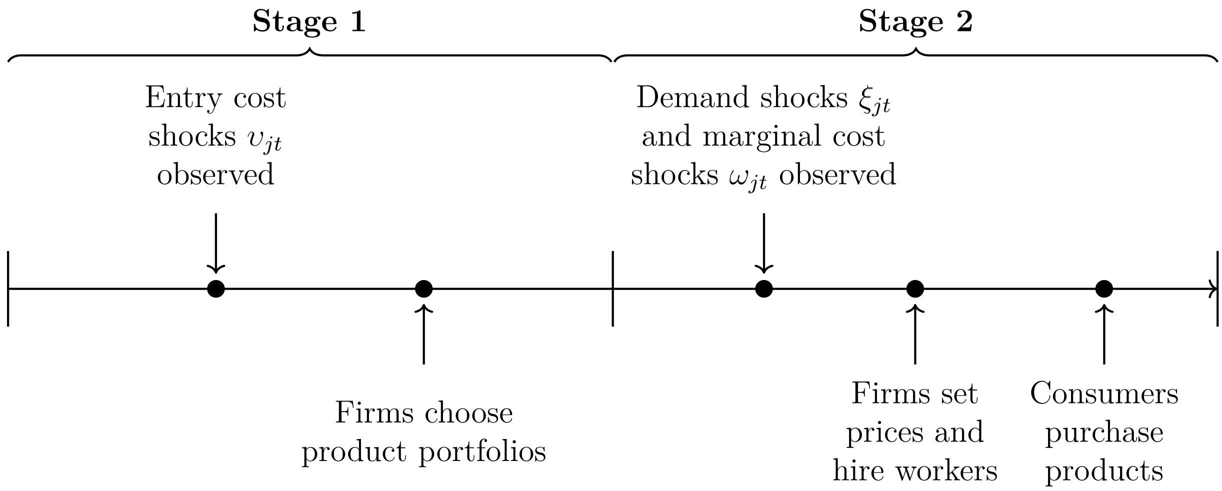



**Figure 8:** Model timeline

of a SPNE but not its uniqueness.

## 4.1 Demand model

Demand is a household-level discrete choice between different clothes washers. The demand model is based on the empirical discrete choice demand literature following S. Berry, Levinsohn, and Pakes (1995) and S. Berry, Levinsohn, and Pakes (2004). Every year, a household makes the choice between different clothes washers on offer in the market as well as not purchasing a clothes washer, i.e. choosing the outside good. This can be thought of as keeping the clothes washer already owned by the household or not owning a clothes washer at all (e.g. using a laundromat).

The utility of household $i$ from buying clothes washer $j$ in year $t$ can be written as

$$u_{ijt} = x_{jt}\beta + \sigma^{FL}\nu_{it}^{FL}x_{jt}^{FL} - (\alpha + \kappa_\alpha \min(\$400\text{k}, z_{it}))p_{jt} + \xi_{jt} + \epsilon_{ijt}\,. \tag{4}$$

The vector $x_{jt}$ includes non-price product characteristics, such as whether a clothes washer can be loaded from the front, whether it is Energy Star certified, or the number of special programs it includes. It also includes indicator variables for the brand and retailer at which the clothes washer was purchased, as well as year fixed effects and brand time trends.[33] $p_{jt}$ is the price of a clothes washer $j$ at time $t$. I denote the set of products among which households can choose at time $t$ as $J_t$.

Average tastes for price and non-price characteristics are captured by $\alpha$ and $\beta$

[33] The full list of product characteristics are the price, the brand repair rate, the total advertising expenditure at the brand level, as well as indicator variables for whether a clothes washer is a front-loader, a Korean front-loader, a front-loader by Fisher & Paykel, a high-end European front-loader (i.e. Asko, Bosch, or Miele), has an agitator, is part of a stacked pair, has a stainless steel exterior, has a white exterior, is Energy Star certified, has additional noise insulation, has a child lockout. Finally, it includes retailer, brand and year fixed effects, as well as linear brand time trends.

respectively. $x_{jt}^{FL}$ is an indicator variable for whether a particular clothes washer is a front-loader. $\nu_{it}^{FL}$ is an i.i.d. draw from a standard normal distribution and represents a household-specific unobserved taste shock for front-loaders. $z_{it}$ is the income of household $i$ at time $t$. Household incomes are capped at \$400,000, as this avoids positive price coefficients for households with very high incomes which can arise when income enters the price coefficient linearly. Incomes beyond this threshold have negligible effects on the estimated demand parameters in practice. $\sigma^{FL}$ measures the dispersion in taste for front-loaders between households. $\kappa_\alpha$ captures how the sensitivity to prices varies with household income.

The remaining part of the utility function consists of an unobservable component constant across households, $\xi_{jt}$, as well as an idiosyncratic household-specific unobservable, $\epsilon_{ijt}$. $\xi_{jt}$ includes any remaining quality differences not captured by the product characteristics and fixed effects, as well as transitory demand shocks that vary between products but are common across households. Finally, $\epsilon_{ijt}$ is an i.i.d. draw from a type I extreme value (Gumbel) distribution.

To simplify notation, I separate utility into the mean utility $\delta_{jt}$ and the household-specific deviation $\mu_{ijt} + \epsilon_{ijt}$. The mean utility includes all utility components that are constant across households. I also define a vector $\theta = (\theta_1, \theta_2)$ which contains all the parameters of the demand model. Let $\theta_1 = (\alpha, \beta)$ contain all linear parameters of the model and $\theta_2 = (\sigma, \kappa)$ all nonlinear parameters. Since I can only identify utilities up to an affine transformation, I normalize the mean utility of the outside good to zero and so the utility of a household for the outside good reduces to $\epsilon_{i0t}$.

The distributional assumptions on the household-specific unobservable allow deriving the familiar logit choice probabilities from this specification. By integrating over the joint distribution of household demographics $P_D(D)$ and the joint distribution of unobserved taste shocks $P_\nu(\nu)$, the model-predicted market share of product $j$ in market $t$ becomes

$$s_{jt} = \int \frac{exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k \in J_t} exp(\delta_{kt} + \mu_{ikt})} P_D(D) P_\nu(\nu) \,. \tag{5}$$

## 4.2 Second stage: pricing

In the second stage, firms observe demand and marginal cost shocks and subsequently set prices. Each firm $f$ chooses prices for the set of products it offers, $J_{ft}$, to maximize its variable profits, given by

$$VP_{ft} = \sum_{j \in J_{ft}} (p_{jt} - mc_{jt}) s_{jt} M_t \,, \tag{6}$$

where $p_{jt}$ denotes the price of $j$ at $t$, $mc_{jt}$ its marginal costs and $M_t$ denotes the total market size. Firms set prices by taking first-order conditions of the variable profit function with respect to the vector of prices for the products they are offering. For each product $j$, the equilibrium price must satisfy

$$p_{jt} = mc_{jt} - [(\nabla_p s \bullet \Lambda)^{-1} s]_{jt}\,, \tag{7}$$

where $\Lambda$ is the ownership matrix and $\nabla_p s$ is the matrix of partial derivatives of market shares with respect to prices.[34]

Marginal costs can be decomposed into several components. In particular, the inverse hyperbolic sine of marginal costs depends on product- and market-specific components in the following way

$$arcsinh(mc_{jt}) = [x_{jt}, ic_{jt}]\gamma + \omega_{jt}\,, \tag{8}$$

where $ic_{jt}$ is a vector of input costs, $\gamma$ captures how product characteristics and input costs affect marginal costs and $\omega_{jt}$ is a transitory product-level unobserved marginal cost shock that is realized and observed by the firms in the pricing stage.[35]

## 4.3 First stage: entry

In the first stage, firms decide which products to offer. At the outset each firm is endowed with a set of potential products it can offer in market $t$, $\mathcal{J}_{ft}$. This can be thought of as the set of products that it is technologically capable of producing. It includes products that it sells already at a different retailer or in a different market and minor adjustments to existing products which it could perform in the short-term. It does not include products for which a firm would need to develop entirely new capabilities (e.g. launching its first front-loading clothes washer).

Introducing a product into the market comes at a fixed and sunk cost. This includes costs related to the final development of a product (e.g. a particular front-loader model), marketing or retailer investments. Empirically, I analyze markets at the yearly level. At the same time, Ashenfelter, Hosken, and Weinberg (2013) show that the volumes of particular clothes washer models rapidly decline after twelve months. It therefore seems plausible that the fixed and sunk cost of introducing a product at a retailer in a particular year is independent of the product portfolio in previous years, since particular models are usually not kept on shelf for longer.

The fixed cost of introducing a new product can be decomposed into a brand- and market-specific component $F_{bt}$ and a mean-zero idiosyncratic product- and market-

[34] The ownership matrix contains information on whether two products are offered by the same firm and so cross-price effects matter for the optimal pricing decision of firm $f$.

[35] The inverse hyperbolic sine is a transformation that approximates the natural logarithm. Its advantage is that zero is part of its definition area and it returns real numbers for negative inputs. See Bellemare and Wichman (2020) for more details.

specific fixed cost shock $\upsilon_{jt}$. Thus $F_{jt} = F_{bt} + \upsilon_{jt}$ and $E[\upsilon_{jt}|j \in \mathcal{J}_{ft}] = 0$. Before deciding on its product portfolio, a firm observes the fixed cost shocks related to all products it could potentially add. It does not yet however observe the second stage marginal cost and demand shocks which I summarize as $e_{jt} = (\xi_{jt}, \omega_{jt})$. Instead, it chooses a product portfolio by trading off expected variable profits and the sum of fixed costs of different products. More specifically, it solves the following maximization problem:

$$\max_{J_{ft} \subseteq \mathcal{J}_{ft}} \{\Pi = E[VP(p)|J_{ft}] - \sum_{j \in J_{ft}} F_{jt}\}\,. \tag{9}$$

Since choosing an optimal product portfolio is a discrete choice, the first order conditions of this profit maximization only hold with inequality.

## 4.4 Demand for domestic workers

Let us now turn to the employment side. The aim of this exercise is to model how the number of U.S. manufacturing jobs changes if we hold production locations and the production technology fixed. I therefore do not model demand and supply in the labor market itself. That is not to say that the number of U.S. clothes washer manufacturing jobs would not change if, for example, wages increased. This would be reflected in the marginal costs of a clothes washer and thus affect equilibrium prices and quantities in the product market.

I assume that firms make longer-term decisions on where to produce which products outside of the model. The share of each product that is produced in the U.S. is therefore exogenously given. Similarly, the production technology $G(\cdot)$ is fixed and the number of manufacturing workers required is linear in the number of clothes washers. The demand for domestic clothes washer manufacturing workers by firm $f$ therefore is

$$LD_{ft} = \sum_{j \in J_{ft}} G(q_{jt}) \times \text{domestic}_{jt}\,. \tag{10}$$

# 5 Estimation

In this section, I describe how to estimate the parameters of the model. As for the model description I proceed in reverse-order, beginning with the demand parameters.

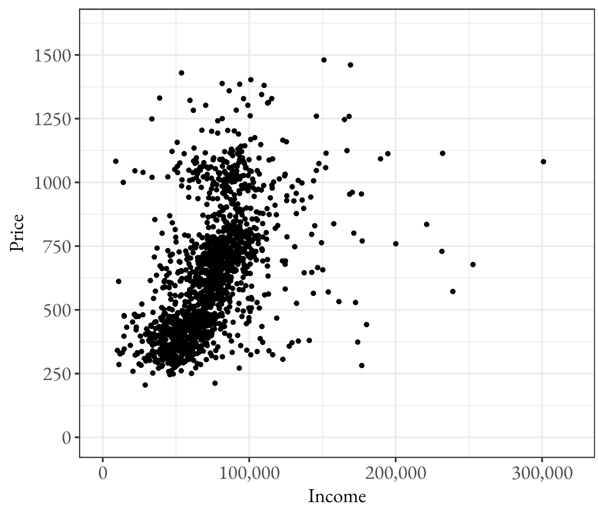
## 5.1 Demand

The estimation of the demand parameters is similar to S. Berry, Levinsohn, and Pakes (2004). In a first step, I estimate the non-linear parameters of the utility function, $\sigma^{FL}$ and $\kappa_\alpha$. I identify these parameters by matching simulated moments to their analogues in the data. Informally, we can think of the data moments as identifying the structural parameters of their simulated equivalent.

The first data moment is based on the correlation between the clothes washer bought being a front-loader and the average share of front-loaders among the second-choice brand. Respondents to the *TraQline* survey are only asked which other brands they considered buying but not which exact model. Some brands carry both front-loaders and top-loaders. However, the share of front-loading clothes washers differs greatly between brands. Furthermore, the correlation between whether the first choice is a front-loader and the share of front-loaders among the second choice brand is important, with a correlation coefficient of 0.4. This suggests that there is a strong unobserved taste for front-loaders among some households, which can affect substitution patterns.

The second data moment is based on the correlation between the household income and the price of a clothes washer bought. Figure 9 shows the correlation between the household income and price. On average, the higher the income of a household, the higher the price of a clothes washer bought. This suggests that high income households are less sensitive to prices.

**Figure 9:** Correlation of average purchaser household income and price by product




Notes: The plot shows the average annual income of households purchasing a particular clothes washer on the x-axis and the average price of that clothes washer on the y-axis. Each point is a product in a particular year. The correlation coefficient between the average income of households purchasing a particular clothes washer and its average price is 0.5.

To estimate the linear parameters of the utility function I first need to estimate the vector of mean utilities, $\delta$. I estimate these by matching simulated market shares for each product to observed market shares. Before estimating the linear utility parameters $\alpha$ and $\beta$, I need to introduce a further assumption:

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

This means that the second stage demand and marginal cost shocks are independent of the non-price product characteristics and the fixed costs of introducing a product. As explained by Eizenberg (2014), this is slightly stronger than the assumption that $e_{jt}$ is realized after products are chosen, since it also means that firms cannot predict $e_{jt}$. This assumption nevertheless seems reasonable, as firms may still predict future costs and demand as they relate to observable characteristics, which I can control for. It only means that firms cannot predict unobservable transitory marginal cost and demand shocks.

Since prices can be adjusted frequently, they are likely correlated with $\xi_{jt}$. As explained in Section 2, I use an instrumental variable based on the production location and the real exchange rate, which affects costs but is otherwise unrelated to demand.

For the linear and non-linear demand parameters, standard errors are clustered at the brand level using the residual bootstrap. First, I estimate the linear and non-linear demand parameters using the original sample. Second, I compute the empirical distribution of demand residuals for every brand. Third, I re-sample demand residuals for every product from the empirical distribution of demand residuals for the respective brand, creating bootstrapped samples. Fourth, I re-estimate the linear and non-linear demand parameters for 100 bootstrapped samples. Finally, I compute the standard error of the parameter estimates using the bootstrapped samples.

## 5.2 Marginal costs and efficiencies

I compute marginal costs for each product by inverting the first order conditions of each firm's profit maximization problem. Under the model assumptions described above, the data are rationalized by a unique marginal cost and markup for each product.

Next, I estimate the parameters of the second-stage supply-side in Equation 8. This estimation serves two purposes. First, it allows me to residualize the inverse hyperbolic sine of marginal costs by the effect of product characteristics and input costs. I can hence split marginal costs into a part that is known to firms when making product entry decisions and the unobserved marginal cost shocks $\omega$.

Second, it provides a data-driven estimate of the marginal cost efficiencies due to changes in the exchange rate and the cost level in different production locations. Since Equation 8 contains the relationship between the real exchange rate and marginal costs, it also allows me to estimate how marginal costs change if the RER changes. By using the post-merger production locations for Maytag products under the two acquisition scenarios (acquisition by Whirlpool and acquisition by Haier), I can estimate how these changes in production locations would affect the RER for Maytag products and their marginal costs.

For the Whirlpool acquisition, I use the observed post-merger production locations for Maytag products by Whirlpool in 2007. Marginal cost efficiencies in this case come from the relocation of front-loader production to Mexico. For the Haier acquisition, I use the publicly discussed relocation plans of Maytag's production to China.

## 5.3 Fixed cost bounds

The entry model in Section 4.3 only provides inequality conditions for profitable entry. It is hence not possibly to point identify entry costs in this setting. I therefore resort to partial identification and seek to estimate bounds on the identified set of fixed entry costs for every brand.

To estimate bounds on the fixed costs of adding a product, I need to determine the set of potential products of each firm. I refer to all products that a firm could have added as the potential products, to the potential products that it actually added as the active products and to the potential products that it chose not to add as the inactive products. Recall that the set of potential products of firm $f$ in market $t$ is denoted as $\mathcal{J}_{ft}$ and the set of active products as $J_{ft}$. I denote the set of inactive products of firm $f$ as $\tilde{J}_{ft}$.

The set of active products are those products that we observe in the data. Before determining the set of inactive products, it is worth remembering that the goal is to estimate the fixed costs of adding or removing a product that is part of the set of products a firm is technologically capable of producing. Thus, if a firm does not have any front-loading washing machines among its active products, I do not consider that it could have added a front-loading washing machine in that particular year. Instead, I exploit the fact that I can distinguish sales at the retailer level and that appliance brand owners introduce different products at different retailers. 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 Best Buy, H. H. Gregg, Home Depot or Lowe's) is an inactive product. I therefore capture the fixed costs related to marketing, getting retail floor space for an additional product or customizing the product for the clientele of a particular retailer, but not of developing new technologies. This is appropriate in this case, since I am interested in estimating how the incentives to make portfolio adjustments change for existing players with already developed product portfolios. Furthermore, the development of new technologies is most likely a multi-year process that does not need to pay off within a year.

The estimation of the bounds on fixed costs resembles the procedure described by Eizenberg (2014). If the product entry that I observe is a pure strategy SPNE, then no firm can profitably deviate unilaterally from this equilibrium. More specifically, this means that no firm can increase its expected profits by unilaterally adding inactive products or removing active products. To estimate bounds on the fixed costs of adding a product, I exploit a subset of the equilibrium conditions, namely that no firm has a profitable one-step deviation.[36]

Let us 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 $j$ that a firm chooses to introduce in equilibrium, an upper-bound on the fixed cost of introducing a product is the expected incremental profit of offering that product holding other products fixed. That is,

$$F_{jt} \leq E_e[VP_{ft}(J^*_{ft}) - VP_{ft}(J^*_{ft} - \mathbf{1}^j_{ft})] \equiv \bar{F}_{jt}\,, \tag{11}$$

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

For each inactive product, a lower-bound on the fixed cost of introducing a product is the expected incremental profit of offering that product holding other products fixed. That is,

$$F_{jt} \geq E_e[VP_{ft}(J^*_{ft} + \mathbf{1}^j_{ft}) - VP_{ft}(J^*_{ft})] \equiv \underline{F}_{jt}\,, \tag{12}$$

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

These two conditions allow estimating the upper-bound on fixed costs of active products and the lower-bound on fixed costs of inactive products. I estimate the expected incremental variable profits using 500 draws from the joint empirical distribution of the demand and marginal cost shocks $e_{jt}$. Ultimately, I am interested in bounds on the brand-level average fixed costs in market $t$, $F_{bt}$. Constructing the upper-bound on $F_{bt}$ only based on active products and the lower-bound based on inactive products is inadmissible, since product portfolio decisions are not independent of $\upsilon_{jt}$, i.e. $E[\upsilon_{jt}|j \in J_{ft}] \neq 0$. Recall, however, that $E[\upsilon_{jt}|j \in \mathcal{J}_{ft}] = 0$, which means that the product-level fixed cost shock has mean zero conditional on products being part of the set of potential products. This means that if we can estimate a lower-bound on the fixed costs of adding active products and an upper-bound on the fixed costs of adding inactive products, we can get an unbiased estimate of bounds on the set of brand-level average fixed costs $F_{bt}$.

To fill the missing bounds, I follow the approach proposed by Eizenberg (2014). The details of the estimation procedure are described in Appendix III.D.

For inference, I estimate the confidence sets using the same bootstrapped samples as for the demand estimation. D. W. K. Andrews (2000) shows that the bootstrap is inconsistent if the parameter is on the boundary of the parameter space, which is defined by inequality conditions. I however use this procedure as a first-order approximation of the consistent confidence sets.

[36] In principle, I could add further restrictions on fixed cost bounds due to the lack of profitable multi-step deviations. In practice, restrictions based on multi-step deviations may be difficult to use, since the additional inequalities would include idiosyncratic fixed cost shocks $\upsilon_{jt}$ for each product.

## 5.4 U.S. employment

Estimating the equilibrium number of U.S. clothes washer manufacturing jobs under different scenarios requires the overall number of employees necessary to manufacture clothes washers in each scenario, as well as the corresponding production locations.

Recall that I assume that the number of employees necessary for the manufacturing process is directly proportional to the number of clothes washers sold. To simplify estimation I also assume that the production technology is linear and constant across products and manufacturers. I use information on the number of employees and clothes washer production from annual reports and news articles to calibrate how many clothes washers a manufacturing worker produces per year on average. I combine this number with the equilibrium quantity of clothes washers sold for each product, to estimate how many manufacturing jobs are necessary globally.[37]

The second step is to estimate the share of clothes washers that are produced in the United States. As described in greater detail in Section 2.3, I construct a granular data set that contains product-level information on the production location of clothes washers produced for the U.S. market. The equilibrium number of U.S. clothes washer manufacturing jobs is therefore the share of global manufacturing jobs multiplied by the share of a product's U.S. production.

To estimate how U.S. employment differs between acquisitions of Maytag by Haier or Whirlpool, I assume that Haier would offshore all Maytag jobs to China; whereas I use the observed post-merger production locations by Whirlpool after its acquisition of Maytag. The latter is necessary to also account for the partial offshoring of former Maytag manufacturing jobs by Whirlpool. Without doing so, I would overestimate the number of jobs maintained by Whirlpool.

# 6 Estimation Results

## 6.1 Demand

Table 5 includes the demand estimates. Column (1) reports the first-stage results, where I regress the endogenous price variable on the instrumental variable (IV) for price, which is the real exchange rate, and include full controls. The results indicate that an increase in the RER by a full unit leads to an increase in clothes washer prices by \$191. The F-statistic is approximately 23, suggesting that the IV is relevant.[38]

[37] I describe this calibration in more detail in the Appendix Section III.E.

[38] I follow I. Andrews, Stock, and Sun (2019), who recommend reporting the effective first-stage F-statistic due to Olea and Pflueger (2013) in cases with a single endogenous regressor. This is equivalent to the Kleibergen-Paap F-statistic in just-identified cases. In the just-identified case with a single endogenous regressor, we can also compare the F-statistic to the Stock and Yogo (2005) critical values.

**Table 5:** Demand estimates

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | First-stage | Reduced form | Logit OLS | Logit IV | Mixed logit IV |
| *Dependent variable:* | Price | $\hat{\delta}_{jt}$ | $\hat{\delta}_{jt}$ | $\hat{\delta}_{jt}$ | |
| *Linear parameter* | | | | | |
| Real exchange rate | 1.909*** | -0.787** | | | |
| | (0.398) | (0.358) | | | |
| Price ('00 2012 $) | | | -0.164** | -0.412** | -0.614*** |
| | | | (0.062) | (0.202) | (0.024) |
| *Non-linear parameter* | | | | | |
| Income effect $\kappa_\alpha$ | | | | | 0.070*** |
| | | | | | (0.011) |
| Unobserved taste $\sigma^{FL}$ | | | | | 2.425*** |
| | | | | | (0.016) |
| Characteristics | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| Retailer FE | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| Brand FE | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| Brand time trends | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| Year FE | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| Observations | 1,590 | 1,590 | 1,586 | 1,590 | 1,590 |
| Kleibergen-Paap F-statistic | 22.979 | | | | |
| Avg. own-price elasticity | | | -0.964 | -2.416 | -3.258 |

Notes: Column (1) presents results for the first stage regression of prices on the real exchange rate. Column (2) includes reduced form estimates for the simple logit model. Column (3) reports demand estimates for the simple logit without instrumenting for price. Column (4) presents demand estimates for the simple logit model using the RER as an instrumental variable for price. Column (5) shows demand estimates for the full mixed logit model presented in Section 4 and using the RER as an instrumental variable for price. For the mixed logit IV model, $\kappa_\alpha$, $\sigma^{FL}$, and $\hat{\delta}_{jt}$ are estimated using simulated method of moments. The remaining linear parameters are estimated using linear IV regression. Standard errors are clustered at the brand level. The own-price elasticity of residual demand is computed at the product level and the average is calculated by weighting products according to their sales volume. Estimates for non-price characteristics are reported in Table A.8. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

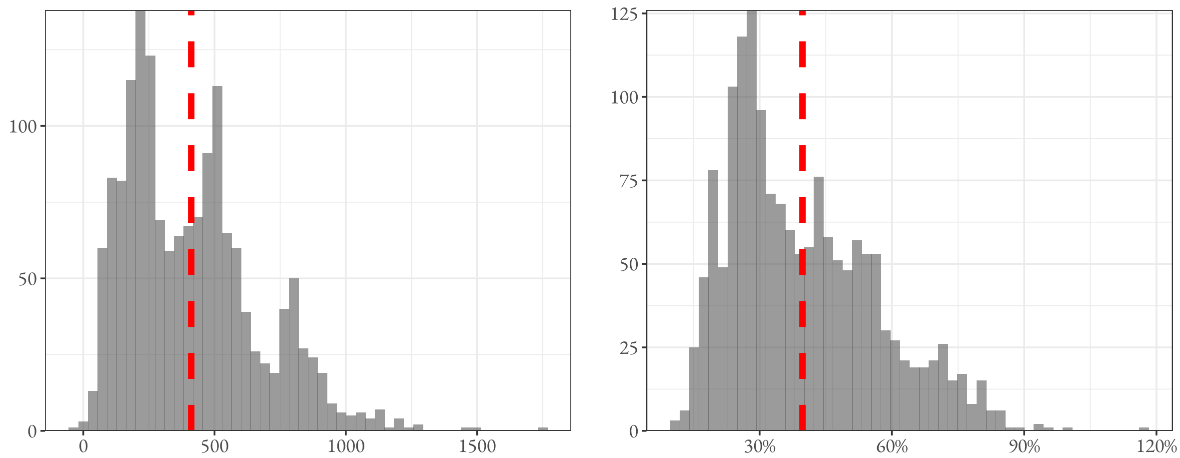
Column (2) includes the reduced form estimates after regressing the outcome variable (the average utility that consumers get from purchasing clothes washer $j$ at time $t$, $\delta_{jt}$) on the instrument. As expected, the higher the RER, the lower the purchasing utility for a consumer. In Columns (3) and (4), I report the price coefficient for the simple logit demand model using OLS and the IV, respectively. By accounting for the endogeneity of prices, the average product-level own-price elasticity of residual demand changes from $-0.96$ to $-2.42$. Finally, I report the price effects for the full mixed logit model using IV in Column (5). The results suggest that there are significantly heterogeneous but correlated preferences across households. As expected, households with a higher household income are less sensitive to prices. Furthermore, households that purchase front-loaders also have an above average unobserved preference for other front-loaders. Accounting for these effects, I estimate that the average own-price elasticity of residual demand for clothes washers further reduces to $-3.26$.[39]

## 6.2 Marginal cost

Figure 10 shows the product-level marginal costs and the Lerner Index for the full observation period. I find that average marginal costs are around \$410 and range between close to zero and around \$1,500. The average Lerner Index in the sample is 40 percent.

**Figure 10:** Product-level distribution of marginal costs and Lerner Index

**(a)** Marginal costs (\$) **(b)** Lerner Index (%)




Notes: The histogram on the left depicts the distribution of product-level marginal cost (in \$) estimates. The dashed red line indicates the average marginal costs. The histogram on the right shows the distribution of the product-level Lerner Index (markup over price). The dashed red line represents the average Lerner Index. Estimates are for the full observation period between 2005 and 2015.

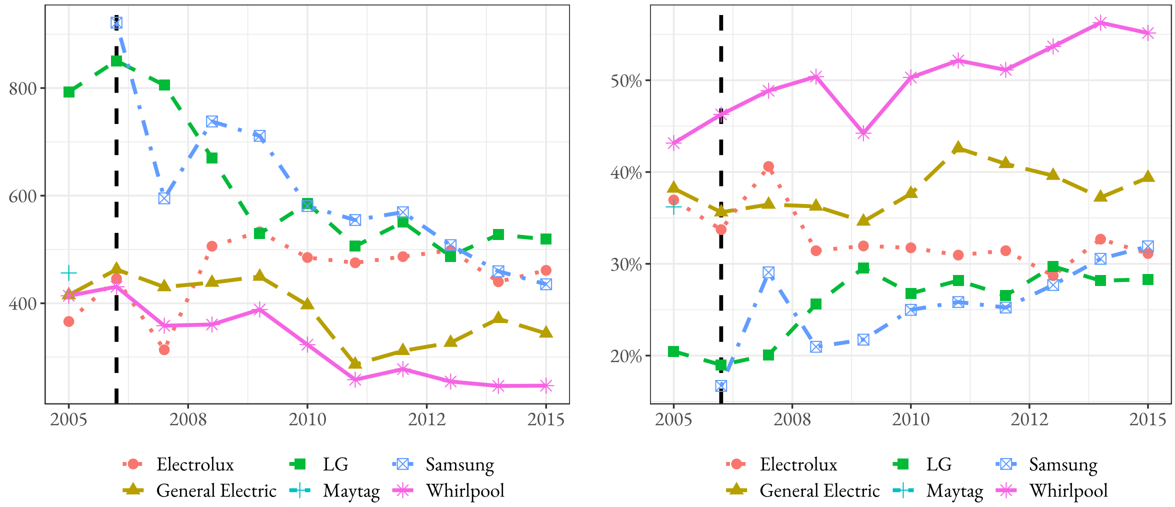
Figure 11 shows the evolution of marginal costs and the Lerner Index by brand

[39]These elasticity estimates are comparable in magnitude to results by Houde (2018), who finds short-term own-price elasticities of residual demand for refrigerators of between $-5.41$ and $-4.15$, depending on household income and using weekly data.

owner over time. After the removal of Maytag as a competitor marginal costs decreased. These decreases in marginal costs cannot all be merger-specific, as we would not expect to see marginal cost efficiencies for competitors as a result of the merger. At the same time profit margins increased.[40] This is also true for Whirlpool, although its Lerner Index after 2006 also includes Maytag, which had a significantly lower Lerner Index than Whirlpool pre-merger.

**Figure 11:** Evolution of marginal cost and Lerner Index by brand owner

**(a)** Marginal costs ($) **(b)** Lerner Index (%)




Notes: The plots show the evolution of marginal costs (left) and the Lerner Index (markup over price; right) by brand owner over time. The vertical line shows the time of the Maytag acquisition by Whirlpool. From 2006 onwards, Whirlpool also includes former Maytag products.

The inverse hyperbolic sine of marginal costs increases by 0.163 if the real exchange rate increases by one unit. Since the inverse hyperbolic sine is similar in form to the logarithmic function, we can approximately interpret this as meaning that marginal costs increase by 16.3 percent if the RER increases by one unit. Table 6 summarizes the estimated average marginal cost efficiencies due to offshoring between the two acquisition scenarios, disaggregated by Maytag's brands. These results suggest only modest marginal cost efficiencies after a Whirlpool acquisition and marginal cost efficiencies of up to 12.2 percent for some brands after a Haier acquisition.

This estimation is most likely too unfavorable to Whirlpool and too favorable to Haier. As previously discussed, Whirlpool made many changes to Maytag's production in the U.S. and cut costs without offshoring most of the production abroad. This would therefore lead to marginal cost efficiencies that are not reflected in the RER. In contrast, the increase in transportation costs and time-to-market which would arise from offshoring production to China is not factored in and is likely to diminish marginal cost efficiencies for Haier. In the alternative specification, I therefore set marginal cost efficiencies for

[40]Large movements in the Lerner Index for Samsung between 2006 and 2007 should be interpreted with caution, since these are based on relatively few Samsung products at the time.

**Table 6:** Marginal cost efficiencies due to offshoring by brand (%)

| **Brand** | **Whirlpool acquisition** | **Haier acquisition** |
|---|---|---|
| Admiral | 0.0 | 12.2 |
| Amana | 1.4 | 11.7 |
| Magic Chef | 0.0 | 11.8 |
| Maytag | 2.1 | 10.7 |

Notes: The table includes estimated marginal cost efficiencies for Maytag products that arise due to offshoring in the two acquisition scenarios. Offshoring efficiencies are based on changes in the real exchange rate due to changes plant network between acquisition scenarios and the relationship between marginal costs and the RER.

both acquisitions to zero. This is likely too favorable to Whirlpool (relative to a Haier acquisition). As demonstrated by the general push towards offshoring at the time of the merger, the location-dependent production costs are too important for it to seem plausible that Whirlpool could completely offset Haier's advantage of producing in China by increasing the efficiency of Maytag's U.S. operations. These two marginal cost scenarios should therefore bound the true trade-off between the two acquisitions.

## 6.3 Fixed cost bounds

Finally, I estimate bounds on the fixed and sunk costs of product entry at the brand-level. Before interpreting these results, it is worth remembering that a product is defined as the combination of a brand, a retailer and major clothes washer characteristics (i.e. the distinction between front-loaders, regular top-loaders and high-efficiency top-loaders). Thus, the fixed cost sets that I estimate should be thought of as the cost of adding a product category (brand and major characteristic combination) at a particular retailer. In practice, this may be the more appropriate way of economically modeling product entry, since, for example, the marketing and sales costs of adding another slightly different Whirlpool front-loader at Sears are likely very low if Sears already offers a Whirlpool front-loader.

Table 7 describes the 95 percent confidence sets on the fixed costs of adding new products. As expected, I find that the range of plausible fixed costs to add products involves higher values for brands with large market shares (e.g. Maytag or Whirlpool) than brands with lower market shares (e.g. KitchenAid, Hotpoint or Westinghouse). This could be because the former are only offered at a retailer if this involves a full range of clothes washers within that product category, requiring more floor space as well as higher marketing expenditures.

**Table 7:** Brand-level fixed costs of adding a product ($M)

| Brand owner | Brand | 95 % confidence sets |
|---|---|---|
| Maytag | Admiral | $[1.4, 1.8]$ |
| | Amana | $[1.0, 2.8]$ |
| | Maytag | $[5.9, 34.8]$ |
| Whirlpool | KitchenAid | $[0.4, 1.0]$ |
| | Roper | $[0.5, 3.4]$ |
| | Whirlpool | $[3.9, 33.1]$ |
| General Electric | General Electric | $[1.7, 20.5]$ |
| | Hotpoint | $[0.3, 1.6]$ |
| Electrolux | Frigidaire | $[1.8, 8.5]$ |
| | Westinghouse | $[0.3, 1.3]$ |
| LG | LG | $[1.5, 25.3]$ |
| Samsung | Samsung | $[1.8, 10.3]$ |

Notes: Brand-level fixed costs of adding or removing a product are based on all active and potential products in 2005 (pre-merger) and 2007 (post-merger). Brand owners listed in the table are based on pre-merger ownership of brands.

# 7 Welfare Effects of the Whirlpool Acquisition

In this section, I combine all of the estimation results so far, to compare the welfare effects of an acquisition of Maytag by Haier to the welfare effects of an acquisition by Whirlpool. In particular, I will focus on assessing how endogenous product portfolio choices, marginal cost efficiencies, and the inclusion of employment effects into the welfare assessment change the relative desirability of each acquisition. Since Haier had close to no presence in the U.S. laundry market prior to the merger, an acquisition by Haier without the marginal cost efficiencies is approximately equivalent to keeping a standalone Maytag in the product market.

## 7.1 Players and potential products

Endogenizing portfolio choices requires deciding who can add products, as well as estimating the set of potential products that players could add.

With endogenous product portfolio choices, I allow Electrolux, General Electric, LG, Maytag, Samsung, and Whirlpool to choose their product portfolios. These are all of the clothes washer manufacturers with a volume share of more than 3 percent. I do not endogenize portfolio decisions for Sears for two reasons: First, since Sears would not introduce Kenmore appliances to other major retailers, it could not react to the increase in prices or removal of products by the merging parties at Home Depot by introducing new Kenmore products at Home Depot. It also means that I do not observe any inactive products and cannot estimate the fixed cost of introducing new products for Sears. Second, since Sears does not manufacture products itself, it can only react by sourcing new products from existing manufacturers. The fact that Sears sourced all of its clothes washers from Whirlpool at the time of the merger might make it particularly difficult to react to price increases and portfolio changes of the merging parties by introducing new products in the short-run. To ease the computational burden, I fix the product portfolios of very small competitors. In practice this should only have minor effects on the welfare estimates.

The set of potential products of each player consist of the sum of their potential products in 2005 (pre-merger) and 2007 (post-merger).[41] Since I observe the acquisition scenario with the highest increase in market power in the data, these observed sets of potential products should be a good approximation of the actual set of potential products. This is because the higher the increase in market power, the lower the intensity of competition becomes and so the higher the incentives are for rivals to add new products. Thus, any product that was not added by rivals after the merger is also unlikely to have been added without the merger. Similarly, the incentives of adding new products was highest for the merging parties pre-merger. Thus, the pre-merger set of potential products should be a good proxy for the actual set of potential products of the merging parties.

Finally, I fix the products of players at smaller retailers that are not part of the five major retailers. This results in 135 potential products for the major manufacturers listed above and 69 exogenously active products (products of non-players and products of players at smaller retailers).

## 7.2 Portfolio choice algorithm

A well-known feature of product entry games is that there can be many potential equilibrium product portfolios. One way of identifying 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 a SPNE of the entry game.[42] In this case, this is computationally infeasible at this time, since there are $2^{135}$ candidate equilibria. I instead leverage specificities of the case at hand to construct a heuristic portfolio choice algorithm. This algorithm is most closely related to the heuristic algorithm by Fan and Yang (2020).

First, I recognize that although firms incur the fixed cost of adding a potential product to their active portfolio every year, they do not start in a vacuum. More specifically, if there are multiple equilibria of the post-merger entry game it appears plausible

[41]Whenever different versions of the same product exist for 2005 and 2007, I choose the 2007 version of the product.

[42]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.

to assume that equilibria closer in the product space to the pre-merger product portfolios are more likely to be realized. Thus, I initialize the portfolio choice algorithm at the pre-merger equilibrium.

After initializing the algorithm, there is an inner and an outer optimization loop to find a one-step equilibrium in portfolio choices. In the inner loop, a particular player computes both the expected change in firm-level profits of adding each inactive product separately to the brand's product portfolio, as well as the expected change in firm-level profits of removing each active product separately. If there is at least one profitable one-step deviation, the player implements this deviation and changes her product portfolio accordingly. I repeat this process until the player has no profitable one-step deviation left. In the outer loop, I repeat this process for each player. The pseudo-code in Appendix V illustrates the steps of the portfolio choice algorithm.

In practice, I can considerably reduce the computational burden by optimizing product portfolios brand-by-brand instead of firm-by-firm. This requires computing fewer potential one-step deviations for every portfolio adjustment. Although I fully take into account how the introduction or removal of a product impacts the firm's expected profit (and not just that of the brand), the downside to this approach is that if products of two brands of the same firm are very close substitutes, the order of play could matter for which product enters. This is unlikely to play an important factor, as firms segment their products by brands and so products within a brand are much closer substitutes than between brands of the same firm.

Another way in which I reduce the computational burden is by only considering one-step deviations and disregarding multi-step deviations. This is necessary because checking for any multi-step deviations is also computationally infeasible in this case.[43] It could thus be that although there is no profitable one-step deviation, there nevertheless exists a profitable multi-step deviation. To assess whether this could be an important problem, it is helpful to consider when such a situation could arise. Since clothes washers are substitutes in the marketplace, if it is not profitable to add a particular clothes washer, it is also not profitable to add that and another potential clothes washer. The same logic applies to the removal of active clothes washers from the product portfolio. It is, however, possible that although adding a particular clothes washer is not profitable, it would be profitable to add the clothes washer and remove another washer from the product portfolio simultaneously. Similarly, it could be that it is profitable to add a clothes washer and remove two washers simultaneously. Overall however it may not be desirable to consider multi-step deviations with many different portfolio adjustments simultaneously, since it is more difficult to make many portfolio adjustments at the same time.

Finally, as I only set identify fixed costs, I repeatedly apply the portfolio choice

[43]To illustrate this point, brands have up to 15 potential products. Checking for all multi-step deviations would thus require checking up to $2^{15} = 32,768$ candidate deviations at each brand iteration.

algorithm for 50 different fixed cost draws for each product. I draw fixed costs from a uniform distribution, where the domain are the confidence sets of fixed costs for each brand. In all scenarios, I report 95 percent confidence sets for the welfare effects across fixed cost draws.

### 7.3 Product portfolio choices

I begin by comparing the product market effects of alternative acquisitions of Maytag by Haier or Whirlpool. Since Haier had close to no U.S. presence prior to the merger, in the product market, an acquisition by Haier without marginal cost efficiencies is approximately equivalent to keeping a standalone Maytag. Whenever I discuss the endogenous choice of the product portfolio, this means that all players can choose active products among the potential products. Since I do not observe realized demand and supply shocks for potential products, I estimate the expected welfare effects based on 500 demand and supply residual draws for each product.

Table 8 summarizes the number of products that firms choose to offer under different acquisition and marginal cost efficiency scenarios. As discussed in Section 5, I distinguish between a scenario in which there are no marginal cost efficiencies after either acquisition and a scenario where I credit Maytag products offshoring efficiencies, due to changes in the real exchange rate of the production locations that are chosen by the respective acquirer.[44] The final two columns show the observed number of products in 2005 and 2007. I consider the former to be the relevant product portfolios of firms under the assumption that there are no portfolio adjustments around the time of the merger. I consider the latter to be the relevant product portfolios of firms under the assumption that there are portfolio adjustments around the time of the merger, but that these adjustments are all independent of any acquisition.

Without marginal cost efficiencies, I find that a Maytag acquisition by Whirlpool leads to fewer products offered belonging to the pre-merger Maytag and Whirlpool. At the same time, for most fixed cost draws, there are slightly more products offered by rivals. Overall, there are fewer products offered.

Next, I compare the differences in endogenous portfolio adjustments between the two potential acquisitions to the differences in observed product portfolios between 2005 and 2007. This comparison is possible, because without efficiencies, in the product market an acquisition by Haier is very similar to no acquisition at all (i.e. the pre-merger market in 2005). I observe a slight increase in the number of products offered by Maytag and a strong increase of products offered by rivals.[45] However I predict a decrease in the number of products offered by Maytag and Whirlpool and a smaller than observed increase of

[44]An overview of the offshoring efficiencies for each acquisition scenario can be found in Table 6.

[45]All products that are marketed under a brand owned by Maytag before the merger (i.e. Admiral, Amana, Magic Chef and Maytag) are denoted as "Maytag".

**Table 8:** Number of products offered by each firm in different acquisition scenarios

| | Endogenous portfolio adjustments | | | | | **No adjust.** | **Indep. adjust.** |
|---|---|---|---|---|---|---|---|
| *Efficiencies:* | No efficiencies | | Offshoring | | | | |
| *Acquirer:* | None / Haier | Whirlpool | None | Haier | Whirlpool | | |
| Maytag | [21.9, 27.5] | [19.8, 25.4] | [21.5, 26.9] | [23.2, 28.2] | [19.7, 25.5] | 21 | 23 |
| Whirlpool | [27.8, 32.8] | [25.1, 30.6] | [27.5, 33.1] | [27.3, 32.1] | [25.5, 30.7] | 27 | 27 |
| LG + Samsung | [4.6, 10.3] | [5.0, 11.4] | [4.7, 10.7] | [4.6, 10.0] | [5.1, 11.1] | 5 | 15 |
| Electrolux + GE | [25.6, 34.2] | [27.2, 35.1] | [25.8, 34.2] | [24.8, 33.6] | [27.4, 35.4] | 34 | 38 |
| Total industry | [106, 117] | [103, 115] | [105, 117] | [105, 117] | [104, 114] | 106 | 128 |

Notes: The first five columns include the 95% confidence sets on the number of products carried by each brand owner depending on who acquires Maytag and whether there are offshoring efficiencies. The final two columns show the number of products had there been no product portfolio adjustments (i.e. observed pre-merger portfolios in 2005) and had all portfolio adjustments been merger-independent, thus always leading to the same post-merger portfolios (i.e. observed post-merger portfolios in 2007). Confidence sets for the expected number of products offered with endogenous portfolio adjustments are based on 50 fixed cost draws for each potential product from a uniform distribution, where the domain are the confidence sets of brand-level fixed costs, and 500 demand and supply residual draws. Maytag includes all products marketed under the brands owned by Maytag pre-acquisition (i.e. Admiral, Amana, Magic Chef and Maytag).

products offered by rivals. This suggests that the observed product portfolio adjustments are only partially driven by the merger and partially driven by other effects, such as an exogenous expansion in the set of potential products. A mere comparison of the market structure pre- and post-acquisition would underestimate the reduction in products by Maytag and Whirlpool and overestimate the expansion of the portfolio by rivals.[46]

## 7.4 Product market effects

Table 9 summarizes the product market effects of Maytag acquisitions by Haier and Whirlpool.[47] I begin by considering the effects of Maytag acquisitions using the pre-merger product portfolios and neglect any type of product portfolio adjustments. Without marginal cost efficiencies, prices after a Whirlpool acquisition increase by 2.7 percent and consumer welfare decreases by 4.9 percent. Total industry profits, as well as the profits of the merging parties, increase, however the increase in profits cannot offset the loss in consumer welfare. With offshoring efficiencies, an acquisition by Haier reduces average industry prices by 1 percent and increases consumer welfare by 3.1 percent, since there is close to no increase in market power. In contrast, with offshoring efficiencies an acquisition by Whirlpool increases prices by 2.6 percent and decreases consumer welfare by 4.3 percent.

[46]This is in line with the descriptive evidence showing that there is also product entry by LG and Samsung in appliance categories unaffected by the Whirlpool acquisition.

[47]Since Haier has nearly no presence in the U.S. clothes washer market pre-merger, without efficiencies, an acquisition by Haier has no economically significant effect on the product market. Simulation results for Haier acquisitions are therefore relegated to Appendix Table A.9.

**Table 9:** Product market effects of Maytag acquisitions by Haier and Whirlpool

| | **No portfolio adjustments** | | | **Merger-independent adjustments** | | | **Endogenous adjustments** | | |
|---|---|---|---|---|---|---|---|---|---|
| *Efficiencies:* | **No efficiencies** | **Offshoring** | | **No efficiencies** | **Offshoring** | | **No efficiencies** | **Offshoring** | |
| *Acquirer:* | Whirlpool | Haier | Whirlpool | Whirlpool | Haier | Whirlpool | Whirlpool | Haier | Whirlpool |
| Average price | 2.7% | -1.0% | 2.6% | 2.9% | -0.9% | 2.7% | | | |
| | [1.7%, 3.7%] | [-2.0%, 0.1%] | [1.5%, 3.6%] | [2.0%, 3.8%] | [-1.0%, -0.8%] | [1.8%, 3.6%] | [1.8%, 5.1%] | [-1.9%, 0.2%] | [1.7%, 4.9%] |
| Consumer welfare | $-131M | $83M | $-116M | $-156M | $61M | $-140M | | | |
| | [$-206M, $-55M] | [$12M, $155M] | [$-191M, $-42M] | [$-237M, $-75M] | [$59M, $63M] | [$-221M, $-59M] | [$-300M, $-197M] | [$58M, $152M] | [$-302M, $-197M] |
| | -4.9% | 3.1% | -4.3% | -4.9% | 1.9% | -4.4% | | | |
| | [-8.4%, -1.3%] | [0.3%, 5.9%] | [-7.8%, -0.9%] | [-8.0%, -1.8%] | [1.9%, 2.0%] | [-7.5%, -1.3%] | [-10.0%, -6.6%] | [1.9%, 5.2%] | [-10.1%, -6.6%] |
| Industry profits | $66M | $14M | $76M | $81M | $26M | $85M | | | |
| | [$27M, $105M] | [$-38M, $65M] | [$31M, $120M] | [$41M, $121M] | [$24M, $27M] | [$46M, $125M] | [$76M, $133M] | [$18M, $74M] | [$78M, $132M] |
| | | | | | | | [5.6%, 10.3%] | [1.4%, 5.8%] | [5.8%, 10.2%] |
| Maytag + Whirlpool profits | $15M | $14M | $33M | $18M | $68M | $30M | | | |
| | [$-23M, $54M] | [$-72M, $99M] | [$-11M, $77M] | [$-18M, $54M] | [$67M, $68M] | [$-6M, $66M] | [$19M, $47M] | [$91M, $119M] | [$20M, $48M] |
| | | | | | | | [2.3%, 6.3%] | [-92.5%, 189.4%] | [2.4%, 6.2%] |

Notes: The first three columns show the effects of a Whirlpool and Haier acquisition of Maytag without product portfolio adjustments. The next three columns show the same comparison for merger-independent portfolio adjustments and the final three columns for endogenous portfolio adjustments. Percentage changes in total profits can only be computed with endogenous adjustments, as this is the only scenario for which I compute fixed costs. Each adjustment scenario includes results without marginal cost efficiencies and with offshoring efficiencies. 95% confidence intervals for effects without product portfolio adjustments and with merger-independent portfolio adjustments are computed using 100 residual bootstrap draws. Confidence sets for the expected effects with endogenous portfolio adjustments are based on 50 fixed cost draws for each potential product from a uniform distribution, where the domain are the confidence sets of brand-level fixed costs, and 500 demand and supply residual draws. Maytag includes all products marketed under the brands owned by Maytag pre-acquisition (i.e. Admiral, Amana, Magic Chef and Maytag). Since Haier has nearly no presence in the U.S. clothes washer market pre-merger, without efficiencies, an acquisition by Haier has no economically significant effect on the product market. Simulation results for Haier acquisitions without efficiencies are therefore omitted for legibility. They can be found in Appendix Table A.9.

Next, I contrast this to the simulated merger effects if future product portfolio adjustments are fully independent of any acquisition.[48] Without marginal cost efficiencies, the predicted price increases of an acquisition by Whirlpool are modestly higher with merger-independent adjustments than without adjustments. Although this leads to a higher loss in consumer welfare in absolute terms, in both cases the Whirlpool acquisition leads to similar relative losses in consumer welfare. This is because the expansion of the overall product portfolio between 2005 and 2007 leads to an increase in the level of consumer welfare under either acquisition scenario. The comparison of both portfolio adjustment cases with offshoring efficiencies is similar.

With fully endogenous portfolio adjustments and no marginal cost efficiencies, the 95 percent confidence sets of the price effects of an acquisition by Whirlpool include modestly higher price increases than the 95 percent confidence intervals with fixed product portfolios. However, the decrease in consumer welfare is considerably higher than without endogenous portfolio adjustments. This is because I predict only a modest increase in the product portfolio by rivals and a larger decrease in the portfolio by Maytag and Whirlpool as a consequence of a Whirlpool acquisition.

If product portfolio adjustments are fully endogenous, offshoring efficiencies make both hypothetical acquisitions better for consumers. Since offshoring efficiencies are larger for Haier than for Whirlpool, this increases the discrepancy in the consumer welfare effects of the two acquisitions.

## 7.5 Trading off workers and consumers

Table 10 summarizes how the two potential acquisitions affect consumers and U.S. employment in different scenarios. Each figure is the difference between the effects of Maytag acquisitions by Whirlpool and Haier. As seen before, a Whirlpool acquisition is always worse for consumers than an acquisition by Haier, since it leads to a higher increase in market power, fewer offshoring efficiencies, only modestly more entry by rivals, and significantly fewer products by the merging parties.

Across all scenarios, an acquisition of Maytag by Whirlpool maintains significantly more jobs in the U.S. than an acquisition by Haier. In Appendix V.C, I decompose this difference in U.S. employment into a relocation effect (due to different plant relocations between acquirers) and a reallocation effect (due to different market share reallocations after each acquisition). Whereas the former leads to more U.S. jobs after a Whirlpool acquisition, the latter pushes in the opposite direction, as foreign competitors gain more market shares after an acquisition by Whirlpool. I find that in this case, most of the change in employment can be explained by the relocation effect.

[48] This could occur if there is an expansion of the set of potential products due to technological progress but that is unrelated to changes in market structure.

**Table 10:** Simulated effects of Maytag acquisitions by Whirlpool vs. Haier

| | **No portfolio adjustments** | | **Merger-independent adjustments** | | **Endogenous adjustments** | |
|---|---|---|---|---|---|---|
| *Efficiencies:* | No efficiencies | Offshoring | No efficiencies | Offshoring | No efficiencies | Offshoring |
| Consumer welfare | \$-130M<br>[\$-205M, \$-55M]<br>$-4.8\%$<br>[$-8.3\%, -1.3\%$] | \$-200M<br>[\$-309M, \$-90M]<br>$-7.2\%$<br>[$-11.9\%, -2.5\%$] | \$-155M<br>[\$-236M, \$-74M]<br>$-4.9\%$<br>[-8.0%, -1.8%] | \$-201M<br>[\$-276M, \$-127M]<br>$-6.2\%$<br>[-9.7%, -2.7%] | [\$-302M, \$-197M]<br>[$-10.1\%, -6.6\%$] | [\$-386M, \$-275M]<br>[-12.5%, -9.0%] |
| Domestic jobs maintained | 1233<br>[677, 1790]<br>24.8%<br>[2.6%, 47.1%] | 1202<br>[627, 1778]<br>24.2%<br>[1.0%, 47.5%] | 1120<br>[644, 1597]<br>22.2%<br>[5.9%, 38.4%] | 1201<br>[645, 1757]<br>24.2%<br>[1.9%, 46.5%] | [1021, 1507]<br>[24.0%, 37.0%] | [1244, 1588]<br>[30.4%, 40.3%] |
| Offsetting job value | \$106k<br>[\$19k, \$192k] | \$166k<br>[\$59k, \$274k] | \$138k<br>[\$63k, \$214k] | \$168k<br>[\$81k, \$255k] | [\$135k, \$316k] | [\$195k, \$316k] |

Notes: The first two columns show the effects of a Whirlpool vs. Haier acquisition of Maytag without product portfolio adjustments. The next two columns show the same comparison for merger-independent portfolio adjustments and the final two columns for endogenous portfolio adjustments. Each adjustment scenario includes results without marginal cost efficiencies and with offshoring efficiencies. 95% confidence intervals for effects without product portfolio adjustments and with merger-independent portfolio adjustments are computed using 100 residual bootstrap draws. Confidence sets for the expected effects with endogenous portfolio adjustments are based on 50 fixed cost draws for each potential product from a uniform distribution, where the domain are the confidence sets of brand-level fixed costs, and 500 demand and supply residual draws. Maytag includes all products marketed under the brands owned by Maytag pre-acquisition (i.e. Admiral, Amana, Magic Chef and Maytag).

I next combine the product market and employment effects and estimate the average job value necessary such that the domestic jobs saved by a Whirlpool acquisition offset the losses in consumer welfare. Overall, this offsetting value is lowest without portfolio adjustments and marginal cost efficiencies and increases for merger-independent and then endogenous adjustments. It increases when accounting for marginal cost efficiencies, since this increases the consumer welfare losses of a Whirlpool compared to a Haier acquisition and makes Maytag products produced by Haier in China relatively more attractive. With endogenous portfolio adjustments and without marginal cost efficiencies, the average offsetting value of each additional job is between \$135,000 and \$316,000 per year.

To gauge whether an acquisition of Maytag by Whirlpool is better for U.S. welfare than an alternative acquisition by Haier requires estimating the consumer welfare and employment effects of the acquisitions for other product markets. Other product markets that Maytag was active in are clothes dryers, dishwashers, ranges, and refrigerators. Without additional product market data, I cannot get a precise estimate of the consumer welfare and employment effects of the merger for these markets. Instead, I make a rough back-of-the-envelope approximation of the order of magnitude of these effects based on the market size and the change in the HHI in these markets compared to clothes washers, as well as reported overall Maytag U.S. employment pre-merger. The details of the estimation can be found in Appendix Section V.D. I find that without marginal cost efficiencies, for appliance categories that are not clothes washers, the average value of a job necessary to offset consumer welfare losses of a Whirlpool acquisition is between \$50,000 and \$79,000 per year. Unsurprisingly, this is significantly lower than for clothes washers, since in all other appliance categories (with the exception of clothes dryers) the increase in the HHI is much lower.

Table 11 summarizes the job value for which employment effects offset consumer

**Table 11:** Comparing offsetting job value to other estimates in the literature

| | Offsetting job value | $\Delta$ Total wage bill | Notes |
|---|---|---|---|
| *Maytag acquisition by Whirlpool vs. Haier* | | | |
| Clothes washers without efficiencies | [$135k, $316k] | | Necessary value of a U.S. clothes washer job to offset losses in consumer welfare |
| Clothes washers with offshoring efficiencies | [$195k, $316k] | | Necessary value of a U.S. clothes washer job to offset losses in consumer welfare |
| Other household appliances | [$50k, $79k] | | Based on back-of-the-envelope calculation described in Appendix Section V.D |
| *Other estimates* | | | |
| Hufbauer and Lowry (2012) | $900k | | Estimate that 2011 U.S. safeguard tariffs on tire imports from China saved 1,200 jobs and cost consumers $1.1 bn |
| Flaaen, Hortacsu and Tintelnot (2020) | $817k | | Estimate that 2018 U.S. global safeguard tariffs on clothes washers created 1,800 jobs and cost consumers $1.6 bn |
| Jaravel and Sager (2020) | [$288k, $478k] | | Estimate price and employment effects of U.S. trade liberalization with China |
| Setzler and Tintelnot (2021) | | $113k | Estimate increase in the total wage bill (from direct and indirect effects) in the local labor market per additional foreign MNE job |

harm and compares these to other estimates from the literature. To offset the consumer harm from trade restrictions, Hufbauer and Lowry (2012) and Flaaen, Hortaçsu, and Tintelnot (2020) estimate that annual job values of between $800,000 and $900,000 are necessary. In comparison, the necessary job values to make a Whirlpool acquisition more attractive than an acquisition by Haier are modest. Results by Jaravel and Sager (2020) for trade liberalization show that trade with China increased U.S. consumer surplus by about $400,000 per displaced job. These are closer in magnitude to the results in this paper.

To determine which acquisition leads to higher U.S. welfare requires determining the value of a job. This is difficult, since even if I knew the wage for each job, it would be insufficient to infer its direct (for the worker that holds the manufacturing job) and indirect (for other workers in the economy) effects. Since I do not have the necessary variation and data to estimate these effects, I compare the offsetting job values to estimates by Setzler and Tintelnot (2021) of the direct and indirect local labor market effects of a job created by a foreign multinational firm.

They find that an additional foreign multinational job increases the total wage bill in a local labor market by $113,000 per year. This includes wages for workers coming from non-employment, as well as the direct effect of the foreign multinational wage premium on employees previously employed at domestic firms.[49] It also includes wage gains for employed workers at domestic firms, as well as wages at newly created domestic jobs.[50]

[49] They estimate that, on average, 87% of foreign multinational employees are previously employed by a domestic firm and that the multinational wage premium is 7%. They estimate that the average earning of a full-time worker is $62,600 at a domestic firm and $75,200 at a foreign multinational.

[50] They estimate a wage increase of 0.15% for workers employed at domestic firms for each one percentage point increase in the share of workers employed at foreign multinationals. Finally, they estimate a total local job multiplier of 1.50, which means 0.50 indirect jobs for every direct job created.

I apply these estimates to all appliance manufacturers, irrespective of their nationality, since Setzler and Tintelnot (2021) find similar wage premia for foreign and domestic multinationals and all of the appliance manufacturers fall in either of the two categories. I do not need to distinguish between local and national employment effects, since I consider each manufacturing job not created domestically to be created abroad.

There are many other positive effects related to an increase in the availability of jobs, that go beyond an increase in wages. Bearing this in mind, I consider the increase in the total wage bill by $\$113,000$ per year as a lower-bound estimate of the value of a U.S. appliance manufacturing job to the U.S. economy. This is at the lower end of the necessary job values to offset losses in consumer welfare for clothes washers with endogenous portfolio adjustments. Since this offsetting value is lower for other appliance categories, I cannot exclude that the sum of consumer welfare and domestic worker income is higher after an acquisition of Maytag by Whirlpool than after an acquisition by Haier. Overall, the aggregate gains to domestic workers from additional jobs are of similar magnitude as the losses in consumer welfare.

## 7.6 Unequal distribution of welfare effects

So far, the analysis focused on how consumers and workers overall are affected by the two alternative acquisitions. However, not all households need to be affected similarly by the acquisitions on the product market, as well as the employment side.

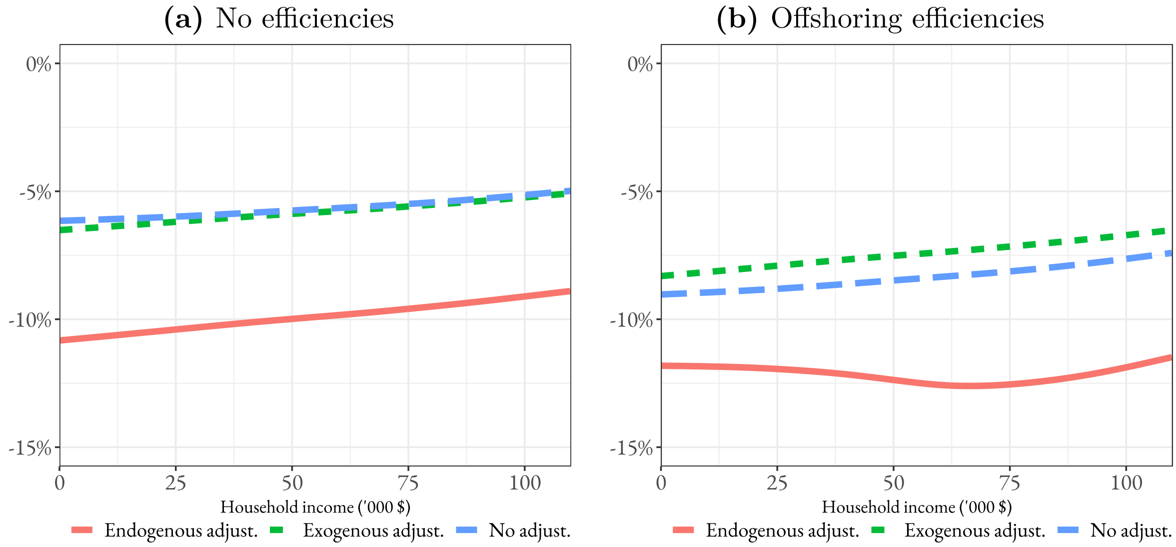
Figure 12 shows the simulated percentage change in consumer welfare between Maytag acquisitions by Whirlpool and Haier, depending on the annual income of a household. Without marginal cost efficiencies, the relative decrease in consumer welfare is highest for households with the lowest household income and the loss in consumer welfare modestly decreases the higher the income.[51] This relationship is steeper with fully endogenous portfolio adjustments than with exogenous adjustments or no adjustments at all.

With offshoring efficiencies, the relationship between household income and the consumer welfare losses after a Whirlpool acquisition of Maytag compared to a Haier acquisition is similar with exogenous or no portfolio adjustments. With endogenous portfolio adjustments, the loss in consumer welfare first increases in household income and then decreases again. This is because with offshoring efficiencies Haier introduces more new products of the former Maytag brand families post-merger. These products are mainly purchased by medium-income households. Foregoing these new Maytag products after an acquisition by Whirlpool thus exacerbates the losses in consumer welfare of a Whirlpool acquisition for households who otherwise would have considered buying these products.

The employment effects of the alternative potential acquisitions are also geograph-

[51] The median annual household income for the simulated households is \$55,000.

**Figure 12:** Consumer welfare change by household income: Whirlpool vs. Haier




Notes: Both graphs show the simulated percentage change in consumer welfare between a Maytag acquisition by Whirlpool and Haier according to household income. The consumer welfare changes are shown for three adjustment scenarios: No product portfolio adjustments, exogenous adjustments, and fully endogenous adjustments. Simulations are based on 1,000 household draws per market. For expositional simplicity, the graphs only show households with an annual income of less than 110,000$, covering 80% of drawn households. In the left panel, no marginal cost efficiencies are credited. In the right panel, offshoring efficiencies are credited to Maytag products. Changes in absolute terms are reported in the Appendix, in Figure A.10.

ically highly unequally distributed. For the U.S. economy as a whole, 1,000 additional clothes washer manufacturing jobs do not have any significant effect on employment or wages. As I showed in Section 3, however, this is different for local labor markets. There, the closure of a manufacturing plants can decrease wages and employment at the county-level even two years after the plant closure. As illustrated in Figure 1, clothes washer manufacturing plants are concentrated in a few counties in Illinois, Iowa, Michigan, Ohio, and South Carolina. Thus, whereas most local labor markets are unaffected by the potential acquisitions, some are strongly affected. Even considering average employment effects at the level of the local labor market masks important heterogeneities in employment effects. Whereas some workers may only mildly be affected by a plant closure, others lose their job and their livelihood.

As I showed above, there is some, albeit modest, heterogeneity in the difference in consumer welfare effects between the two potential acquisitions. These are also unlikely to differ greatly geographically. In contrast, there are large heterogeneities in the geographic distribution of employment effects. This has implications for optimal policy. If household preferences are such that households have diminishing marginal utility of income and employment effects are not concentrated among the very wealthy, then an acquisition by Whirlpool may be domestic welfare improving, even if the increase in the total domestic wage bill as compared to a Haier acquisition is lower than the relative consumer welfare loss. Furthermore, other non-wage considerations related to job loss, such as mental or physical health, can improve the domestic welfare effects of a Whirlpool as compared to a Haier acquisition.

Finally, political considerations cannot be neglected completely. Whereas a loss in consumer welfare in the clothes washer market by $20 is unlikely to affect how voters cast their ballot, direct and indirect employment effects can. Thus, facilitating an acquisition of Maytag by Whirlpool as opposed to Haier can be politically more attractive.

# 8 Simplifying Estimation with Proprietary Data

There are two aspects of the analysis discussed so far which make it less attractive to implement in ex ante merger control. First, estimating fixed cost bounds is costly in terms of programming and computational time. Only identifying bounds on the fixed cost of product entry also reduces the precision of the estimation. Second, using observed post-merger entry to estimate the set of potential products is infeasible in ex ante merger analysis. Luckily, better data usually more easily available to competition authorities than to researchers can solve these problems.

To avoid the estimation of fixed costs, competition authorities can use market surveys and internal documents from market participants to form estimates of the costs of adding new products. Such a calibration exercise can simplify the overall analysis and potentially also lead to tighter fixed cost bounds.

A similar approach can be taken to estimate the set of potential products and their characteristics. Instead of having to observe what products are added by market participants after a merger, competition authorities can rely on market surveys and internal documents to identify the potential product pipeline.

This does not mean, however, that it is possible to completely forego the methods described in this paper to predict post-merger product portfolios. Estimating which products enter conditional on demand, a set of potential products, and associated marginal costs and fixed costs of adding a product remains necessary. Although using an algorithm to predict which products enter after a hypothetical merger cannot be substituted with market surveys or internal documents, these, as well as industry-specific knowledge, can help refine the heuristic entry algorithm. This can improve the reliability of portfolio choice predictions in practice.

# 9 Conclusion

This paper proposes a model to analyze the consumer welfare and employment effects of different potential product market mergers in the presence of foreign entry and describes how to estimate its structural parameters. To account for how mergers change the incentives to introduce new products, I allow firms to endogenously adjust their product portfolios. To account for employment effects, I model how the equilibrium in the product market affects the number of (domestic) employees required to manufacture the product. Structurally estimating the parameters of the model is not only possible for ex post merger evaluations, but also for prospective merger analysis. To facilitate its use in merger control, I describe how data that could be requested by competition authorities can be used to reduce the estimation burden and increase the precision of the estimates.

I apply the model to analyze the acquisition of Maytag by Whirlpool in the U.S. household appliance industry. Although the Department of Justice cleared the merger on the grounds that foreign product entry would sufficiently constrain the merging parties, the merger decreased consumer welfare by more than 5 percent. This is true when comparing it to no merger, as well as an alternative acquisition of Maytag by Haier. With endogenous product portfolio adjustments, rivals modestly increase the number of products they offer after a Whirlpool acquisition and the merging parties moderately decrease the number of products. Overall, endogenous portfolio adjustments increase the consumer harm of a Whirlpool acquisition. Rival product entry is therefore an insufficient constraint on the merging parties even in this landmark case where an entry defense was at the heart of the clearance decision.

By estimating the domestic employment effects of the two potential acquisitions, I investigate whether these could have made an acquisition by Whirlpool more desirable in terms of U.S. domestic welfare. I find that a Whirlpool acquisition leads to the preservation of more U.S. manufacturing jobs. I calculate the average value of a job necessary for domestic employment effects to offset the losses in consumer welfare. A comparison to estimates by Setzler and Tintelnot (2021) on the direct and indirect local labor market effects of new jobs by multinational firms leads to the conclusion that the aggregate gains to domestic workers from additional jobs is of similar magnitude as the consumer welfare losses. Overall, I cannot exclude that an acquisition of Maytag by Whirlpool leads to higher domestic welfare than an alternative acquisition by Haier.

This has important implications for policy. Since the employment effects of a product market merger can be of first order importance, these should not be ignored in merger analysis. Blocking acquisitions that could lead to the offshoring of jobs or allowing anti-competitive mergers that could lead to the preservation of jobs compared to an alternative acquisition may still not be optimal.

Instead, the framework laid out in this paper could be used to identify mergers in which employment effects are of first order importance. Whilst the merger decision could still be taken based on the consumer welfare standard, this would identify cases where there may be a need for complementary labor market policies.

# References


Alfaro-Ureña, A., Manelici, I., and Vasquez, J. P. (2021). "The Effects of Multinationals on Workers: Evidence from Costa Rican Microdata." *mimeo*.

Andrews, D. W. K. (2000). "Inconsistency of the Bootstrap when a Parameter is on the Boundary of the Parameter Space." *Econometrica*, 68 (2): pp. 399–405.

Andrews, I., Stock, J., and Sun, L. (2019). "Weak Instruments in IV Regression: Theory and Practice." *Annual Review of Economics*, 11: pp. 727–753.

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

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

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review*, 103 (6): pp. 2121–2168.

Bai, L. and Stumpner, S. (2019). "Estimating US Consumer Gains from Chinese Imports." *American Economic Review: Insights*, 1 (2): pp. 209–224.

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

— (2008b). "Reinvigorating Horizontal Merger Enforcement." In: ed. by R. Pitofsky. Oxford University Press.

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

Bellemare, M. F. and Wichman, C. J. (2020). "Elasticities and the Inverse Hyperbolic Sine Transformation." *Oxford Bulletin of Economics and Statistics*, 82 (1): pp. 50–61.

Benkard, C. L., Yurukoglu, A., and Zhang, A. L. (2021). "Concentration in Product Markets." *NBER Working Paper 28745*.

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

Berry, S., Levinsohn, J., and Pakes, A. (1995). "Automobile Prices in Market Equilibrium." *Econometrica*, 63 (4): pp. 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): pp. 68–105.

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

Brunner, D., Heiss, F., Romahn, A., and Weiser, C. (2020). “Reliable Estimation of Random Coefficient Logit Demand Models.” *mimeo.*

Cabral, L. M. (2003). “Horizontal mergers with free-entry: why cost efficiencies may be a weak defense and asset sales a poor remedy.” *International Journal of Industrial Organization*, 21 (5): pp. 607–623.

Caradonna, P., Miller, N. H., and Sheu, G. (2021). “Mergers, Entry, and Consumer Welfare.” *Georgetown McDonough School of Business Research Paper 3537135.*

Card, D., Cardoso, A. R., Heining, J., and Kline, P. (2018). “Firms and Labor Market Inequality: Evidence and Some Theory.” *Journal of Labor Economics*, 36 (1): pp. 13–17.

Ciliberto, F., Murry, C., and Tamer, E. (2021). “Market Structure and Competition in Airline Markets.” *Journal of Political Economy*, 129 (11): pp. 2995–3038.

Conlon, C. and Gortmaker, J. (2020). “Best practices for differentiated products demand estimation with PyBLP.” *The RAND Journal of Economics*, 51 (4): pp. 1108–1161.

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

Draganska, M., Mazzeo, M. J., and Seim, K. (2009). “Beyond plain vanilla: Modeling joint product assortment and pricing decisions.” *Quantitative Marketing and Economics*, 7 (2): pp. 105–146.

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

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

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

Fan, Y. and Yang, C. (2020). “Competition, Product Proliferation, and Welfare: A Study of the US Smartphone Market.” *American Economic Journal: Microeconomics*, 12 (2): pp. 99–134.

— (2021). “Merger, Product Variety and Firm Entry: the Retail Craft Beer Market in California.” *mimeo.*

Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). “The Next Generation of the Penn World Table.” *American Economic Review*, 105 (10): pp. 3150–82.

Flaaen, A., Hortaçsu, A., and Tintelnot, F. (2020). “The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines.” *American Economic Review*, 110 (7): pp. 2103–27.

Garrido, F. (2020). “Mergers Between Multi-Product Firms With Endogenous Variety: Theory and an Application to the RTE-Cereal Industry.” *mimeo.*

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

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

Grieco, P. L., Murry, C., and Yurukoglu, A. (2021). "The Evolution of Market Power in the Us Auto Industry." *NBER Working Paper 29013*.

Houde, S. (2018). "How consumers respond to product certification and the value of energy information." *The RAND Journal of Economics*, 49 (2): pp. 453–477.

Hufbauer, G. and Lowry, S. (2012). "US Tire Tariffs: Saving Few Jobs at High Cost." *Peterson Institute for International Economics*.

Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993). "Earnings Losses of Displaced Workers." *The American Economic Review*, 83 (4): pp. 685–709.

Jaravel, X. and Sager, E. (2020). "What are the Price Effects of Trade? Evidence from the U.S. and Implications for Quantitative Trade Models." *mimeo*.

Jeziorski, P. (2015). "Empirical Model of Dynamic Merger Enforcement–Choosing Ownership Caps in US Radio." *mimeo*.

Lacetera, N. and Sydnor, J. (2015). "Would You Buy a Honda Made in the United States? The Impact of Production Location on Manufacturing Quality." 97 (4): pp. 855–876.

Lee, R. S. and Pakes, A. (2009). "Multiple Equilibria and Selection by Learning in an Applied Setting." *Economics Letters*, 104 (1): pp. 13–16.

Li, S., Mazur, J., Park, Y., Roberts, J., Sweeting, A., and Zhang, J. (Forthcoming). "Repositioning and Market Power After Airline Mergers." *The RAND Journal of Economics*.

Marinescu, I. and Hovenkamp, H. (2019). "Anticompetitive Mergers in Labor Markets." *Indiana Law Journal*, 94 (3): p. 1031.

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

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

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

Miller, N. H. and Weinberg, M. C. (2017). "Understanding the Price Effects of the MillerCoors Joint Venture." *Econometrica*, 85 (6): pp. 1763–1791.

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

Nevo, A. (2001). "Measuring Market Power in the Ready-to-Eat Cereal Industry." *Econometrica*, 69 (2): pp. 307–342.

Nocke, V. and Whinston, M. (2020). "Concentration Screens for Horizontal Mergers." *NBER Working Paper 27533*.

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

Olea, J. L. M. and Pflueger, C. (2013). "A Robust Test for Weak Instruments." *Journal of Business & Economic Statistics*, 31 (3): pp. 358–369.

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

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

Prager, E. and Schmitt, M. (2021). "Employer Consolidation and Wages: Evidence from Hospitals." *American Economic Review*, 111 (2): pp. 397–427.

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

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

Setzler, B. and Tintelnot, F. (2021). "The Effects of Foreign Multinationals on Workers and Firms in the United States." *The Quarterly Journal of Economics*, 136 (3): pp. 1943–1991.

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

Stock, J. and Yogo, M. (2005). *Testing for Weak Instruments in Linear IV Regression; Identification and Inference for Econometric Models*. Ed. by D. W. K. Andrews. New York: Cambridge University Press, pp. 80–108.

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

Werden, G. J. and Froeb, L. M. (1998). "The Entry-Inducing Effects of Horizontal Mergers: An Exploratory Analysis." *The Journal of Industrial Economics*, 46 (4): pp. 525–543.

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

# Appendix

## I Appendix to Section 2: Details on data set construction

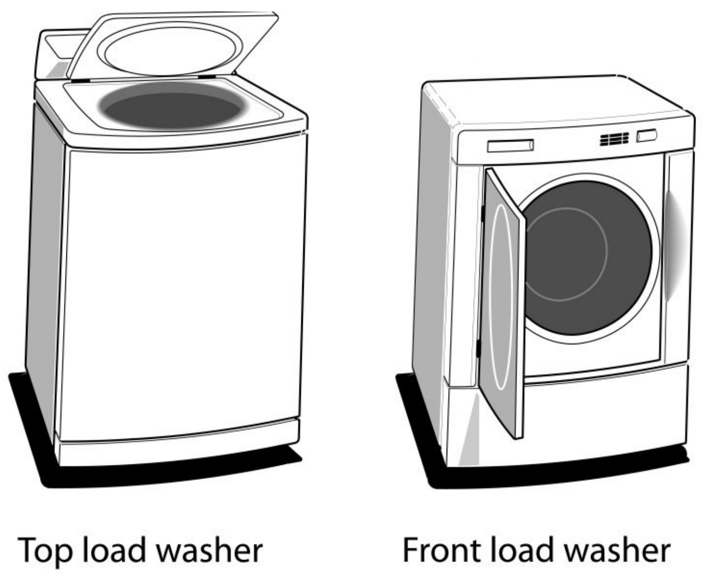
### I.A Product market data set

In this section, we add further details on the construction of the product market data set.

**Product data.** As described in Section 2, for clothes washers, a product is defined as the combination of a brand, a retailer and whether the clothes washer is a front-loader, a regular top-loader (with an agitator) or a high-efficiency top-loader (without an agitator). For clothes washers, these are the key differentiating characteristics between products.

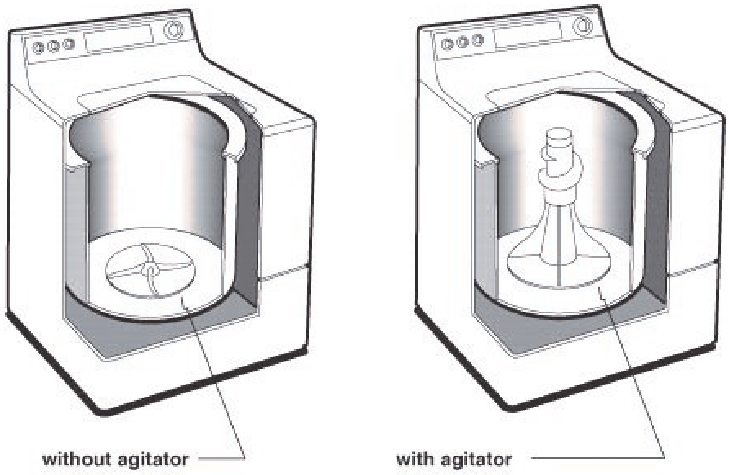
Figure A.1 illustrates the difference between a front-loader and a top-loader. Whether the former can be loaded from the front, the latter is loaded from the top. The former can therefore be stacked (i.e. a front-loading dryer can be placed on top of a front-loading washing machine), is more water and energy efficient, cleans better, and is usually more expensive than top-loaders. The latter can never be stacked, however, for top-loaders, there is an important distinction related to whether they have an agitator, which is illustrated in Figure A.2. top-loaders without an agitator are also called high-efficiency top-loaders. In all respects but stacking, they are in between regular top-loaders and front-loaders.[52]

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




[52]See, for example, McCabe (2016) for a detailed comparison of the different clothes washer types.

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




Within a market (here, national at the yearly-level), I group responses that are the same along these three dimensions.[53] Doing so, I end up with 2,939 products between 2005 and 2015. Using this product definition, many products are often very small and based only on a single responding household. Some responses also do not contain information on the brand. I therefore drop all products whose brand response is "Other Brands" or "Store Brand/Generic", as well as all products with a volume share of the clothes washer market of less than 0.01 percent. This results in a final product data set with 1,590 products. Throughout the years, the remaining products account for between 97.3 and 99.0 percent of the volume share of all clothes washer sales in the *TraQline* data. Dropping very rare products should therefore not bias the estimation results.

For other characteristics, which are only available for a random subset of *TraQline* respondents, I calculate the within-group average of responses for that characteristic. These include whether a clothes washer is part of a stacked pair, whether its exterior is made of stainless steel, is white, or of a different color, whether it is Energy Star certified, has additional noise insulation or a child lockout, as well as the number of special programs it has.

**Household income.** Whereas the CPS data includes the exact income of the sampled households, the *TraQline* data only includes an income range for each household. To estimate how the price sensitivity of households depends on household income using a single parameter only, I need an exact income for each household. For this, I randomly draw a household income for each respondent based on the empirical distribution of household incomes and the income range that the household falls into.

This involves the following steps:

[53] For 2006, I classify Maytag products as belonging to Whirlpool also for the first quarter, where the acquisition was not yet carried out. This is to avoid artificially inflating the number of clothes washer products in that year. Also, since merger talks were public since mid-2005, it seems unlikely that Maytag and Whirlpool would still compete heavily in the first quarter of 2006.

1. Compute the mid-point of the non-overlapping household income buckets for each response.

2. For each year, fit a log-normal income distribution to the observed household-level income range mid-points.

3. Draw $1,000,000$ incomes from the fitted log-normal income distribution.

4. Allocate each income draw to a particular income bucket.

5. For each household, sample with replacement an income from the set of incomes that correspond to its income bucket.

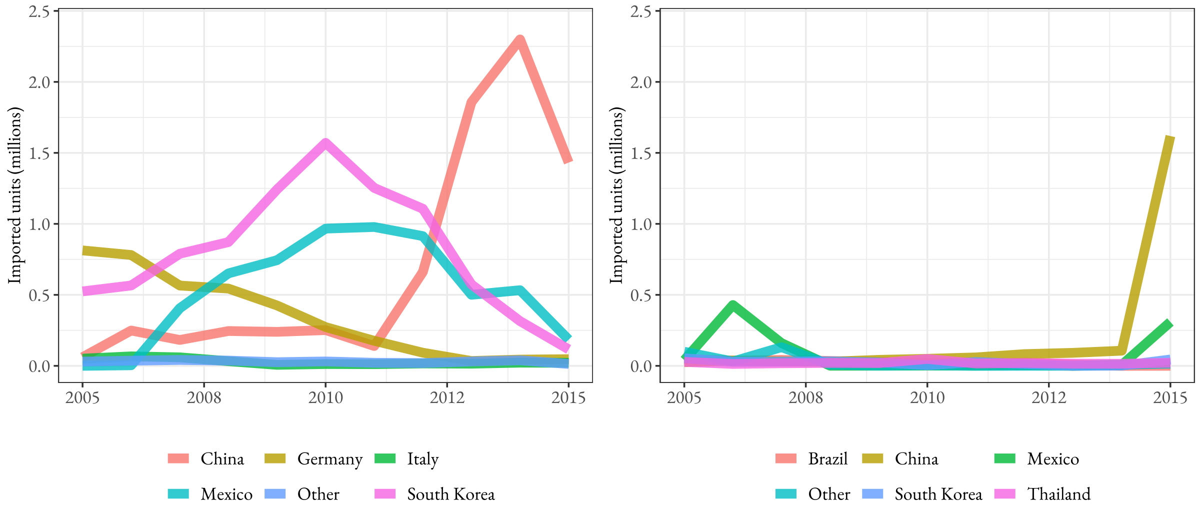
## I.B Plant locations and plant location weights

**Plant locations.** Constructing the data set on plants manufacturing clothes washers for the U.S. market involves three steps: First, I use information from various sources, such as annual reports, news articles or the United States International Trade Commission's (USITC) anti-dumping hearing transcripts to identify the location of clothes washer plants by the major manufacturers. In many cases, this is insufficient to know whether a plant produces clothes washers for the U.S. or for another market. Second, I use information on the general imports of front-loader and top-loader clothes washers to the U.S. split by source country over time. I use this data to eliminate any plants that cannot plausibly produce substantive volumes for the U.S. market. Finally, I use this data to verify that there are production plants that can plausibly be responsible for the imported volumes for each country from which the U.S. imports substantial numbers of clothes washers.

Figure A.3 shows the evolution of annual imports of front-loaders and top-loaders into the U.S., split by source country. Across the sample period more than half of the front-loaders sold in the U.S. are imported. In 2005, Germany is the largest exporter of front-loaders into the United States. These are not produced by a German manufacturer, but by Whirlpool in its plant in Schorndorf, which was closed in 2012. Until 2012, LG and Samsung imported many of its front-loaders from South Korea and, like other manufacturers such as General Electric or Whirlpool, also from Mexico. After the imposition of anti-dumping duties on large residential clothes washers from Mexico and South Korea in 2012, imports from both countries declined and LG and Samsung moved their production to China (see Flaaen, Hortaçsu, and Tintelnot, 2020 for an in-depth discussion). In contrast, no country exported more than $50,000$ top-loaders to the U.S. until 2011, aside from a temporary spike in top-loader imports from Mexico in 2006 and 2007. Thereafter, LG and Samsung begin increasing their sales of top-loaders in the U.S. and import most of these from China.

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

**(a)** front-loaders **(b)** top-loaders



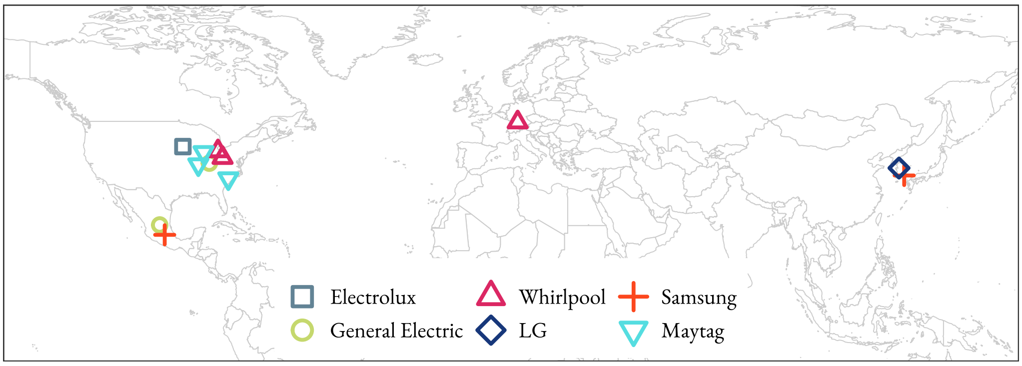

Notes: The left panel plots the annual general imports in terms of volume of front-loader washing machines (HS8450110080, HS8450200080, HS8450200090) imported into the U.S. by source country. The right panel plots the annual general imports in terms of volume of top-loader washing machines (HS8450110040, HS8450200040) imported into the U.S. by source country. The graphs include the top fix importing countries for each product class and groups all other importing countries into "Other". The data comes from the United States International Trade Commission.

For reference, according to Appliance Portrait (2006), 9.3 million clothes washers were sold across the U.S. in 2005. Of those, according to the *TraQline* data, around one-third are front-loaders and the rest top-loaders. The share of front-loaders gradually increased to over 40 percent in 2010 and then decreased again to around 25 percent in 2015. This suggests that although substantial amounts of front-loaders were imported into the U.S. throughout the sample period, most top-loaders were produced domestically.

By combining the clothes washer plant locations of major manufacturers with the USITC import data, I can identify which plants manufacture clothes washers for the U.S. market. Figures A.4, A.5, A.6, and A.7 show the locations of clothes washer plants for all manufacturers that have a volume share of more than 3 percent of the U.S. clothes washer market in any year in the sample.

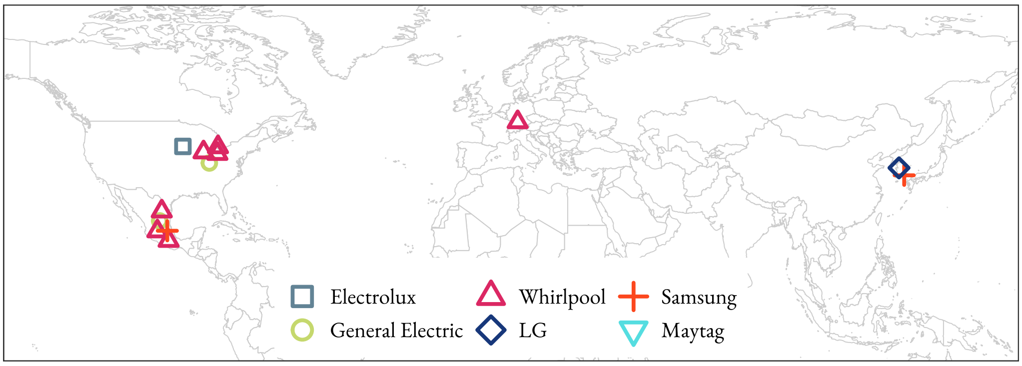
**Plant location weights.** Finally, Table A.1 summarizes the plant location weights used to calculate the average real exchange rate for each product. Based on the plant locations, the aggregate USITC import data shown above, and the firm-level clothes washer imports for 2012 until 2015 based on PIERS bill of landing data and reported in Flaaen, Hortaçsu, and Tintelnot (2020), these are best estimates of which share of a product is sourced from which country in a particular year.

**Figure A.4:** Clothes washer plant locations 2005



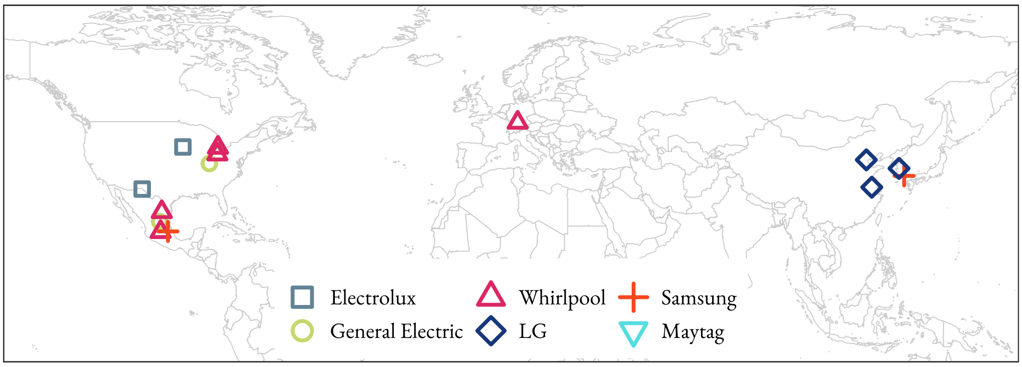

Notes: The map shows all plants manufacturing clothes washers for the U.S. market in 2005 by manufacturers with a market share of more than 3 percent in any year in the sample.

**Figure A.5:** Clothes washer plants manufacturing for the U.S. market, 2007



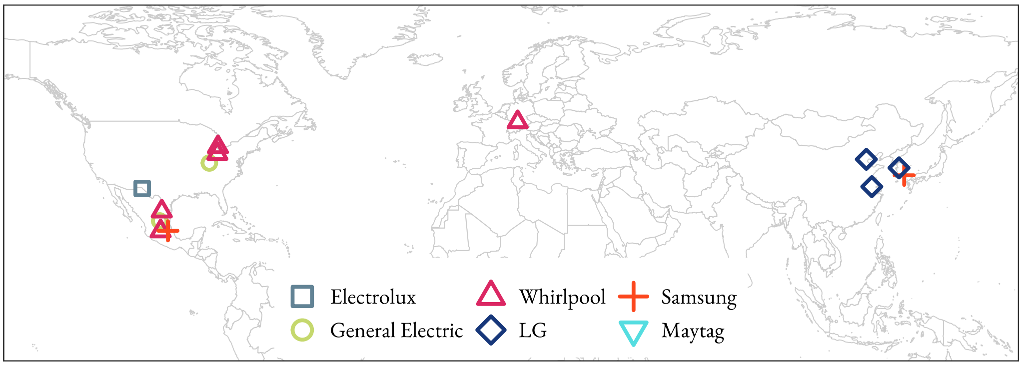

Notes: The map shows all plants manufacturing clothes washers for the U.S. market in 2007 by manufacturers with a market share of more than 3 percent in any year in the sample.

**Figure A.6:** Clothes washer plants manufacturing for the U.S. market, 2009




Notes: The map shows all plants manufacturing clothes washers for the U.S. market in 2009 by manufacturers with a market share of more than 3 percent in any year in the sample.

**Figure A.7:** Clothes washer plants manufacturing for the U.S. market, 2011




Notes: The map shows all plants manufacturing clothes washers for the U.S. market in 2011 by manufacturers with a market share of more than 3 percent in any year in the sample.

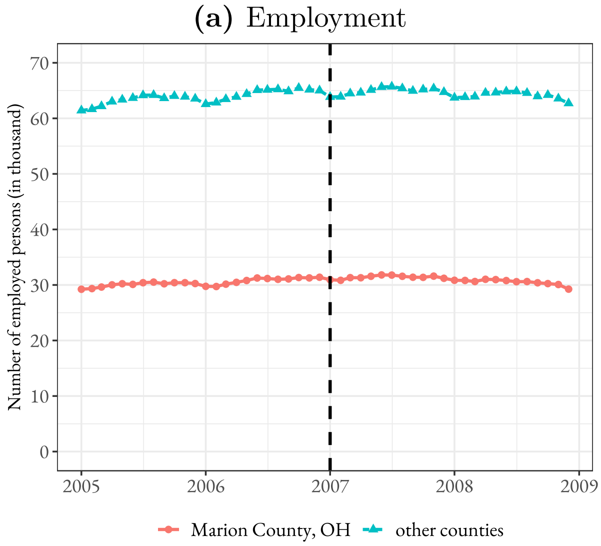
**Table A.1:** Plant location weights

| 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 | All brands | Front Loader | 2005 | | 1 | | | |
| Whirlpool | All other WP brands | Front Loader | 2006-2007 | | 1 | | | |
| Whirlpool | All other WP brands | Front Loader | 2008-2010 | | 0.5 | 0.5 | | |
| Whirlpool | All brands | Front Loader | 2011 | | 0.33 | 0.33 | | 0.33 |
| Whirlpool | All brands | Front Loader | 2012-2015 | | | | | 1 |
| Whirlpool | Admiral, Amana, Maytag | Front Loader | 2006-2010 | | | 1 | | |
| Whirlpool | Admiral, Amana, Maytag | Front Loader | 2010 | | | 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 | | | | 1 | |
| Samsung | All brands | Front Loader | 2012 | 0.5 | | | 0.5 | |
| 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 |

# II Appendix to Section 3: Further descriptive evidence

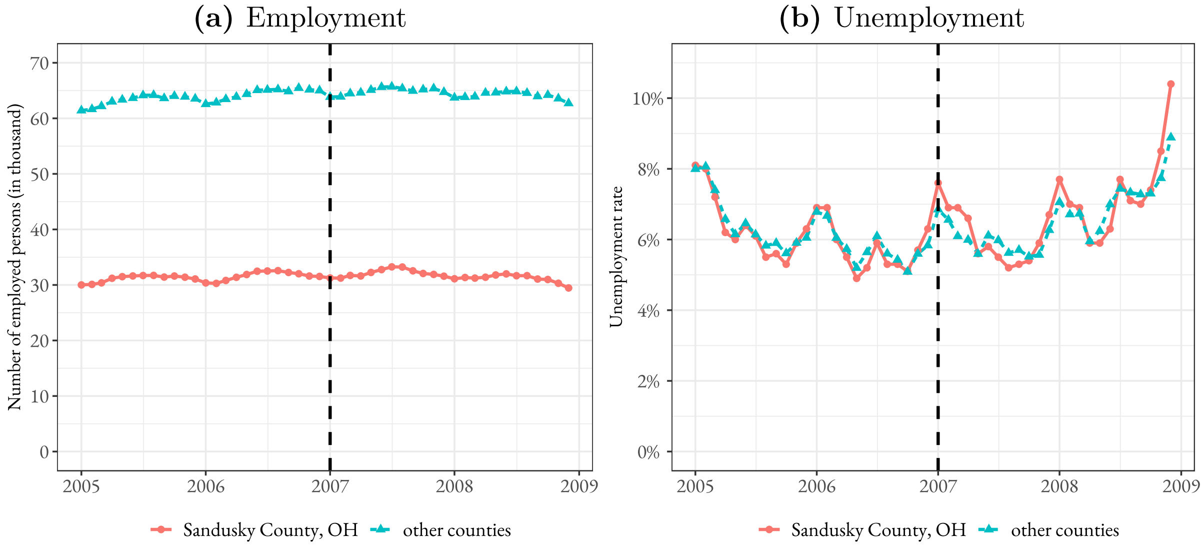
## II.A Labor market effects

**Figure A.8:** Labor market effects of new jobs in Marion County, OH




Notes: The solid red lines show the evolution of the total number of employed persons and the unemployment rate in percentages in Marion County, Ohio, respectively. The dashed blue lines show the average number of employed persons and the unemployment rate by county for all other counties in Ohio, respectively. The vertical dashed lines indicate the shut down of operations on 31 December 2006.

**Figure A.9:** Labor market effects of new jobs in Sandusky County, OH




Notes: The solid red lines show the evolution of the total number of employed persons and the unemployment rate in percentages in Sandusky County, Ohio, respectively. The dashed blue lines show the average number of employed persons and the unemployment rate by county for all other counties in Ohio, respectively. The vertical dashed lines indicate the shut down of operations on 31 December 2006.

**Table A.2:** Reduced form labor market effects of plant and HQ closures (private sector)

| | Employment (persons) | | Wages ($) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Plant & HQ closure × $\mathbb{1}$ (year = 2007) | -1099*** | | -3385*** | |
| | [-1275,-923] | | [-3619,-3150] | |
| Plant & HQ closure × $\mathbb{1}$ (year = 2008) | -1621*** | | -8788*** | |
| | [-1844,-1397] | | [-9071,-8505] | |
| Plant closure × $\mathbb{1}$ (year = 2007) | | -299** | | -384 |
| | | [-532,-66] | | [-1208,439] |
| Plant closure × $\mathbb{1}$ (year = 2008) | | -323** | | -523 |
| | | [-642,-5] | | [-1373,327] |
| County fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Observations | 4,752 | 8,448 | 1,584 | 2,804 |
| Mean outcome in treated counties | 9,328 | 11,151 | 34,022 | 23,274 |

Notes: Columns (1) and (2) compare the absolute number of private sector employees in treated counties to all other counties in the same state. Columns (3) and (4) compare the average annualized gross wage of private sector employees in treated counties to all other counties in the same state. Columns (1) and (3) compare Jasper County (county of Newton) to all other counties in Iowa. Columns (2) and (4) compare White County (Searcy) and Williamson County (Herrin) to all other counties in Arkansas and Illinois. Cook County (county of Chicago), is omitted from any analyses involving Illinois. 95% confidence intervals are reported in parentheses. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table A.3:** Reduced form labor market effects of new jobs (private sector)

| | Employment (persons) | Wages ($) |
|---|---|---|
| | (1) | (2) |
| New jobs × $\mathbb{1}$ (year = 2007) | 434* | -180 |
| | [-51,918] | [-414,54] |
| New jobs × $\mathbb{1}$ (year = 2008) | 724* | -492 |
| | [-71,1518] | [-1196,211] |
| County fixed effects | Yes | Yes |
| Time fixed effects | Yes | Yes |
| Observations | 4,224 | 1,396 |
| Mean outcome in treated counties | 22,373 | 31,604 |

Notes: Column (1) compares the absolute number of private sector employees in Marion County (Marion) and Sandusky County (Clyde) to all other counties in Ohio. Column (2) compares the average annualized gross wage of private sector employees in Marion County and Sandusky County to all other counties in Marion County and Sandusky County. 95% confidence intervals are reported in parentheses. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table A.4:** Reduced form labor market effects of plant and HQ closures (private sector excl. manufacturing)

| | Employment (persons) | | Wages ($) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Plant & HQ closure × $\mathbb{1}$ (year = 2007) | -389*** | | -2096*** | |
| | [-554,-223] | | [-2311,-1881] | |
| Plant & HQ closure × $\mathbb{1}$ (year = 2008) | -360*** | | -1774*** | |
| | [-557,-162] | | [-2023,-1524] | |
| Plant closure × $\mathbb{1}$ (year = 2007) | | -11 | | 37 |
| | | [-550,529] | | [-518,591] |
| Plant closure × $\mathbb{1}$ (year = 2008) | | -28 | | 54 |
| | | [-424,368] | | [-836,943] |
| County fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Observations | 4,752 | 8,448 | 1,584 | 2,816 |
| Mean outcome in treated counties | 7,144 | 9,660 | 26,431 | 22,599 |

Notes: Columns (1) and (2) compare the absolute number of private sector employees excluding manufacturing in treated counties to all other counties in the same state. Columns (3) and (4) compare the average annualized gross wage of private sector employees excluding manufacturing in treated counties to all other counties in the same state. Columns (1) and (3) compare Jasper County (county of Newton) to all other counties in Iowa. Columns (2) and (4) compare White County (Searcy) and Williamson County (Herrin) to all other counties in Arkansas and Illinois. Cook County (county of Chicago), is omitted from any analyses involving Illinois. 95% confidence intervals are reported in parentheses. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table A.5:** Reduced form labor market effects of new jobs (private sector excl. manufacturing)

| | Employment (persons) | Wages ($) |
|---|---|---|
| | (1) | (2) |
| New jobs × $\mathbb{1}$ (year = 2007) | -227 | -430* |
| | [-650,196] | [-923,63] |
| New jobs × $\mathbb{1}$ (year = 2008) | -96 | -441** |
| | [-648,455] | [-806,-77] |
| County fixed effects | Yes | Yes |
| Time fixed effects | Yes | Yes |
| Observations | 4,224 | 1,408 |
| Mean outcome in treated counties | 22,373 | 31,604 |

Notes: Column (1) compares the absolute number of private sector employees excluding manufacturing in Marion County (Marion) and Sandusky County (Clyde) to all other counties in Ohio. Column (2) compares the average annualized gross wage of private sector employees excluding manufacturing in Marion County and Sandusky County to all other counties in Marion County and Sandusky County. 95% confidence intervals are reported in parentheses. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table A.6:** Reduced form labor market effects of plant and HQ closures (manufacturing sector)

| | Employment (persons) | | Wages ($) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Plant & HQ closure × $\mathbb{1}$ (year = 2007) | -710*** | | -802*** | |
| | [-754,-666] | | [-1259,-344] | |
| Plant & HQ closure × $\mathbb{1}$ (year = 2008) | -1261*** | | -22255*** | |
| | [-1324,-1198] | | [-22858,-21652] | |
| Plant closure × $\mathbb{1}$ (year = 2007) | | -288 | | -1080 |
| | | [-758,181] | | [-4105,1945] |
| Plant closure × $\mathbb{1}$ (year = 2008) | | -296 | | -2638*** |
| | | [-824,233] | | [-3870,-1406] |
| County fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Observations | 4,752 | 8,448 | 1,572 | 2,659 |
| Mean outcome in treated counties | 2,185 | 1,491 | 58,368 | 27,603 |

Notes: Columns (1) and (2) compare the absolute number of employees in the manufacturing industry in treated counties to all other counties in the same state. Columns (3) and (4) compare the average annualized gross wage of employees in the manufacturing industry in treated counties to all other counties in the same state. Columns (1) and (3) compare Jasper County (county of Newton) to all other counties in Iowa. Columns (2) and (4) compare White County (Searcy) and Williamson County (Herrin) to all other counties in Arkansas and Illinois. Cook County (county of Chicago), is omitted from any analyses involving Illinois. 95% confidence intervals are reported in parentheses. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table A.7:** Reduced form labor market effects of new jobs (manufacturing sector)

| | Employment (persons) | Wages ($) |
|---|---|---|
| | (1) | (2) |
| New jobs × $\mathbb{1}$ (year = 2007) | 661*** | -232 |
| | [377,944] | [-1640,1177] |
| New jobs × $\mathbb{1}$ (year = 2008) | 820*** | -965 |
| | [507,1133] | [-3074,1144] |
| County fixed effects | Yes | Yes |
| Time fixed effects | Yes | Yes |
| Observations | 4,224 | 1,403 |
| Mean outcome in treated counties | 7,938 | 41,344 |

Notes: Column (1) compares the absolute number of employees in the manufacturing industry in Marion County (Marion) and Sandusky County (Clyde) to all other counties in Ohio. Column (2) compares the average annualized gross wage of number of employees in the manufacturing industry in Marion County and Sandusky County to all other counties in Marion County and Sandusky County. 95% confidence intervals are reported in parentheses. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# III Appendix to Section 5: Details on the estimation procedures

## III.A Details on estimating product characteristics for potential products

Potential products are all products that brand owners added to the market (active products), as well as all products that they could have added but did not (inactive products). Estimating the former is easy, since we can simply observe these in the market. Estimating the latter is more complicated.

The focus of the analysis in this paper lies on the decision of firms to add or remove products that they are technologically already capable of making. For example, if a firm does not carry front-loading washing machines, these will also not be part of its potential products. If, for example, Maytag sells regular top-loading washing machines under its Amana brand at Best Buy and Lowe's, but not at other major retailers, Amana regular top-loaders at other major retailers are potential products.[54]

Product characteristics can mildly vary between retailers. That is, Amana top-loaders sold at Best Buy might modestly differ in their characteristics compared to Amana top-loaders sold at Lowe's. In the example, Amana regular top-loaders at Sears are an inactive product. To determine the exact product characteristics of this inactive product,

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

I need to decide whether to attribute it the characteristics of the Amana regular top-loader sold at Best Buy or at Lowe's.

Whenever a particular combination of brand and key characteristic exists at two or more retailers, I use the following ordering of "closest" retailers to match other product characteristics:

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

## III.B Details on the demand estimation

The estimation of the demand parameters follows S. Berry, Levinsohn, and Pakes (2004) and proceeds in two steps. First, I search for estimates $\hat{\kappa}_\alpha$ and $\hat{\sigma}_{FL}$ (jointly denoted by $\hat{\theta}_2$ of the non-linear parameters, as well as of the vector of mean utilities $\delta$. Next, I estimate $\hat{\beta}$ for the vector of linear demand parameters. Wherever possible, I implement the best practices described by Conlon and Gortmaker (2020). For notational simplicity, I omit the time subscript $t$ in this section. The details of the technical implementation should thus be seen as valid for a single market $t$ and then repeated and averaged over markets.

The estimation of the non-linear 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 non-linear parameters. In the outer loop, I search for the non-linear parameters that minimize the objective function, solving the inner loop at each step.

The first set of moments equates the observed market shares in the data with the simulated market shares from the demand model. To get an estimate $\hat{\delta}$ of the mean utilities, I proceed as follows: First, as described by S. Berry (1994), I 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 $\theta$.[55] Second, I use the fixed-point formulation due to S. 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 this is not guaranteed to converge, whenever convergence fails, I revert to the contraction mapping in S. Berry, Levinsohn, and Pakes (1995) which has guaranteed convergence. Finally, I speed up the inversion of market shares by using the reformulation

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

of the contraction mapping in terms of consumer-specific choice probabilities for the outside option, described by Brunner, Heiss, Romahn, and Weiser (2020).

To estimate the market shares implied by the estimate $\hat{\theta}$ of the parameter vector, the model and the data, I need to solve the integral in Equation 5. As is standard in the literature, I approximate this integral using Monte Carlo simulations by drawing household demographics and unobserved taste shocks from the joint empirical distribution for 1000 households. Household demographics come from the CPS. I draw unobserved taste shocks from a standard normal distribution, using scrambled Halton draws (see Owen, 2017).

The second set of moments fits the covariance between the price of the first-choice clothes washer and the average income of households purchasing the product. I compute the moment as follows

$$\sum_j \frac{n_j}{n} p_j \left\{ \left( \frac{1}{n_j} \sum_{is.t.y_i^1=j} z_i \right) - E\left[ z | y^1 = j, \theta \right] \right\} , \tag{13}$$

where $J$ continues to denote a product, $n$ denotes the total number of households, $n_j$ denotes the number of households buying good $j$, $y_i^1$ denotes the first choice product of household $i$, $p_j$ continues to denote the price of product $j$, and $z_i$ the income of household $i$.

The third set of moments fits the covariance between whether the first-choice clothes washer is a front-loader and the share of front-loaders among products of the second choice brand. In contrast to S. Berry, Levinsohn, and Pakes (2004), I do not observe the exact second-choice product but only the second-choice brand. In particular, I use the following moment condition

$$\sum_j \left( \frac{n_j}{n} x_j^{FL} \sum_{b' \neq b_j} x_{b'}^{FL} \left\{ \frac{n_{jb'}}{n_j} - E\left[ \mathbb{1}\left( b^2 = b' | y^1 = j, \theta \right) \right] \right\} \right) , \tag{14}$$

where $b$ denotes a brand, $b_j$ denotes the brand of product $j$, $b^2$ denotes the brand of the second choice, $x_j^{FL}$ indicates whether product $j$ is a front-loader and $x_{b'}^{FL}$ denotes the volume-weighted share of front-loaders among products sold of brand $b$.

The objective function that I minimize in the outer loop to estimate $\hat{\theta}_2$ consists of the moments in Equations 13 and 14. Since there are two nonlinear parameters and two moment conditions, the parameters are just-identified and we estimate $\hat{\theta}_2$ using the method of simulated moments. I therefore estimate

$$\hat{\theta}_{2,MSM} = \operatorname{argmin} \hat{m}\left(\theta_2\right)' \hat{m}\left(\theta_2\right) . \tag{15}$$

Solving the minimization problem above does not only allow recovering the nonlinear parameters of the demand model, but also the mean utilities $\hat{\delta}$. In the final step, I estimate the linear parameters of the demand model using the following specification:

$$\hat{\delta}_j = x_j\beta - \alpha p_j + \xi_j \,. \tag{16}$$

As explained in Section 5, I assume that the non-price product characteristics are independent of unobserved quality differences $\xi_j$, whereas the price can be correlated with these unobserved differences. To solve the endogeneity problem, I use an instrumental variables estimator, where the product-level real exchange rate serves as a cost shifting instrumental variable for price, as described in Section 2.

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

To compute the total market size, I assume that every seventh household is a potential purchaser of a clothes washer in a particular year. According to Consumer Reports, in 2009 the average life expectancy of a clothes washer was ten years. Many households will consider buying a clothes washer already before the end of the life expectancy of their washer, e.g. to get a new washer with novel features. Some households will consider new washing machines for multiple years. Households that recently purchased a washer are unlikely to be on the lookout for a new one immediately. It therefore seems plausible that the true market size is somewhere between a fifth and a tenth of the number of households. The results are robust to alternative market size assumptions.

To compute firm profits, consumer welfare and estimate entry cost bounds in Dollar terms for the U.S. population, I need to scale the estimates by the number of households that are in the market for clothes washers in a particular year. There are two alternative estimation methods: We can take the total number of U.S. households in a particular year and assume that the market size is one seventh of these households. Alternatively, I can use estimates of the annual total clothes washers shipped as reported by Appliance Portrait and divide this by the share of the inside good. Both methods yield similar results for the years around the merger date and so I assume that the total market size in the U.S. is around 15 million households.

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

Both, the estimation of fixed costs, and the heuristic entry algorithm require computing the expected profits of firms for many different product portfolios. This is computationally costly and since it has to be repeated many times, speeding up this process is crucial. In the following, I briefly describe the key elements that helped speed up the computations for this paper.[56]

[56] As noted in the Online Appendix to Wollmann (2018), implementing the computations in Julia has significant speed advantages, as it can handle loop commands at comparable speed to “vectorized” code

**Computing equilibrium prices.** Each draw of the second-stage marginal cost and demand shocks $e_{jt}$ requires re-estimating the equilibrium price vector for all active products. Since I use 500 draws of $e_{jt}$ to approximate the expected variable profits for a single product portfolio, it is also necessary to re-compute equilibrium prices 500 times for each product portfolio. Speeding up this process is therefore crucial. Furthermore, not all methods to re-compute equilibrium prices necessarily converge.

Morrow and Skerlos (2011) compare different numerical methods to re-compute equilibrium prices using the Nash-Bertrand first order conditions. They find that applying Newton methods to this problem is reliable but slow. On the other hand, they show that fixed point iteration on the BLP-markup equation need not converge and is slow. Instead, they propose a reformulated markup equation, the $\zeta$-markup, which is fast and reliable. I therefore compute equilibrium prices by using fixed point iteration on the $\zeta$-markup equation.

**Drawing $e_{jt}$.** The heuristic algorithm to choose product portfolios requires comparing the expected profits of the current product portfolio to the expected profits of any product portfolio that is within a one-step change of the current product portfolio. This involves revisiting the same product portfolios many times.

An important feature of the heuristic portfolio choice algorithm is to use the same $e_{jt}$ draws for the same product when computing the expected profits of different product portfolios. In terms of economics, this is desirable because there is no good reason for why a firm should form its expectation about demand and cost shocks for a product differently based on what other products are in the market. In terms of computations, this is desirable because it means that I only need to compute expected profits of all firms for a given set of product portfolios once. Every time that the algorithm re-visits the particular set of product portfolios, I can re-use the memorized expected profits and do not need to re-compute equilibrium prices and expected profits.

## III.D Details on the fixed cost estimation

I follow the approach proposed by Eizenberg (2014) and fill the missing bounds by adding two further assumptions.

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

Assumption 2 states that the fixed costs associated with introducing a new product have a bounded support. This assumption does not need to be fulfilled in all contexts. If $F_{jt}$ is the cost of developing a new breakthrough technology, it could be that no money in the world makes the necessary invention possible. Since I consider $F_{jt}$ to be the cost of

in Matlab.

introducing a product at a new retailer and developing new products interior to a firm's technological capability frontier, it seems plausible that there exists an upper-bound to the necessary fixed costs. At the same time, the cost of developing and introducing a new product in this context should never be negative and so the existence of a lower-bound of the fixed cost support, $F_b^L$, is an innocuous assumption.

**Assumption 3.** $[F_b^L, F_b^U] \subset$ *supp(expected change in variable profit due to the elimination or addition of a single product of brand b).*

Assumption 3 adds further restrictions on the support of $F_{jt}$. For each brand $b$, the support of the fixed costs of introducing any potential product is contained within the support of expected changes in variable profits of firm $f$ if any potential product of brand $b$ is introduced. The intuition behind this assumption is quite simple. If fixed costs of introducing different potential products of a particular brand come from the same distribution and there exists a blockbuster product that increases expected variable products of the firm so much, that it would always be introduced, then I observe this product as an active product in the data and the expected change in variable profit of adding this product must be higher than the fixed cost of introducing any potential product. Similarly, if there exists a product that has such a small impact on the expected change in variable profit, such that it would never be introduced, then I will always observe this product as an inactive product and the expected change in variable profit of adding this product must be lower than the fixed cost of introducing any potential product.

With these additional assumptions, I can fill the missing upper- and lower-bounds on the fixed costs of potential products. I fill the missing lower-bound on fixed costs for active products by using the minimum change in firm-level expected variable profits among inactive products of the same brand. I fill the missing upper-bound on fixed costs for inactive products by using the maximum change in firm-level expected variable profits among active products of the same brand. The product-level bounds on fixed costs for active and inactive products are defined as

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

Since $E[\upsilon_{jt}|j \in \mathcal{J}_{ft}] = 0$, and with estimates on the upper- and lower-bound on fixed costs for all $j \in \mathcal{J}_{ft}$, I can now apply an unconditional expectation, such that

$$E[L_{jt}(\theta)] \leq F_{bt} \leq E[U_{jt}(\theta)] \quad \forall j \in \mathcal{J}_{bt}\,. \tag{17}$$

To estimate the set in 17, I replace the true parameter vector $\theta$ by the first stage estimator $\hat{\theta}$ and estimate the change in firm-level variable profits of removing any active product and adding any inactive product in the data. I use $\min_{j \in \tilde{J}_{bt}}\{\underline{F}_{jt}(\hat{\theta})\}$ as an estimator for $VP^L_{bt}(\theta)$ and $\max_{j \in J_{bt}}\{\bar{F}_{jt}(\hat{\theta})\}$ as an estimator for $VP^U_{bt}(\theta)$.

Finally, I compute the within brand and market sample average across $L_{jt}(\hat{\theta})$ and $U_{jt}(\hat{\theta})$, to estimate bounds on the set of brand- and market-level fixed costs. This estimation procedure produces unbiased estimates and overall leads to wide and conservative fixed cost bounds.

## III.E Details on the employment calibration

To simulate the employment effects of the different hypothetical acquisitions, I need an estimate of how many clothes washers a manufacturing worker produces on average per year. Since I do not have systematic data on employment by manufacturer and appliance category, I calibrate the number of clothes washers produced by manufacturing workers based on different sources.

In 2005, Maytag produced clothes washers and dryers in Newton, Iowa (1,000 manufacturing jobs) and Herrin, Illinois (1,000 manufacturing jobs) and dryers in Searcy, Arkansas (700 manufacturing jobs).[57] In addition, there was a small plant manufacturing clothes washers and dryers in Florence, South Carolina (60 manufacturing jobs).[58] According to Appliance Portrait (2006), Maytag shipped 1.75 million clothes washers and 1.6 million dryers in 2005. On average, these are around 1,200 clothes washers and dryers per manufacturing worker per year.

In 2011, the Whirlpool plant manufacturing front-loading clothes washers in Schorndorf, Germany, had 500 employees and produced 200,000 clothes washers.[59] This amounts to 400 clothes washers per manufacturing worker per year.

To simplify matters, I assume that the number of employees necessary to produce clothes washers linearly increases in the number of clothes washers and that this technology is constant over time and across manufacturers, products, and production locations. With richer data and depending on the institutional context, all of these assumptions can be relaxed.

Based on the evidence described above, I calibrate that a manufacturing worker produces on average around 1,000 clothes washers per year. Among clothes dryers, top-loading washers, and front-loading washers, the first are the simplest products to produce and the last the most complex. It therefore seems plausible that the estimate for Whirlpool front-loaders is an overall underestimate of the number of clothes washers produced by worker and the estimate based on Maytag washers and dryers an overesti-

[57] See `https://www.nbcnews.com/id/wbna12718867`.

[58] See `https://www.twice.com/news/maytag-close-florence-laundry-facility-27876`.

[59] See `https://www.stuttgarter-zeitung.de/inhalt.bauknecht-in-schorndorf-konzern-gibt-den-standort-auf.2559fd28-6719-48b9-a055-5956c7f61c03.html`.

mate. Either way, choosing a relatively high number of clothes washers per manufacturing worker is a conservative approach, since it likely underestimates the employment effects of either acquisition.

# IV Appendix to Section 6: Further results of the structural estimation

## IV.A Demand estimation

**Table A.8:** Detailed estimates of linear demand parameters

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | First-stage | Reduced form | Logit OLS | Logit IV | Mixed logit IV |
| *Dependent variable:* | Price | $\hat{\delta}_{jt}$ | $\hat{\delta}_{jt}$ | $\hat{\delta}_{jt}$ | $\hat{\delta}_{jt}$ |
| Real exchange rate | 1.909*** | -0.787** | | | |
| | (0.398) | (0.358) | | | |
| Price ('00 2012 $) | | | -0.164** | -0.412** | -0.614*** |
| | | | (0.062) | (0.202) | (0.024) |
| Front-loader | 0.174 | 0.267 | 0.358 | 0.339 | -0.686*** |
| | (0.205) | (0.267) | (0.244) | (0.215) | (0.019) |
| Korean | -0.563*** | 1.746*** | 1.569*** | 1.514*** | 1.483*** |
| front loader | (0.179) | (0.353) | (0.349) | (0.348) | (0.011) |
| Fisher & Paykel | -4.506*** | -0.624 | -1.455*** | -2.481*** | -3.116*** |
| front-loader | (0.331) | (0.412) | (0.480) | (0.859) | (0.093) |
| European high-end | 0.071 | 1.235*** | 1.192*** | 1.264* | 1.272*** |
| front-loader | (1.311) | (0.314) | (0.438) | (0.715) | (0.032) |
| Agitator | -2.510*** | 0.952*** | 0.540** | -0.083 | -0.449*** |
| | (0.276) | (0.270) | (0.252) | (0.532) | (0.060) |
| Stacked pair | 0.493* | -0.225 | -0.147 | -0.022 | 0.027** |
| | (0.280) | (0.149) | (0.149) | (0.202) | (0.011) |
| Stainless steel | 0.481 | -0.052 | 0.009 | 0.146 | 0.180*** |
| exterior | (0.603) | (0.247) | (0.270) | (0.362) | (0.011) |
| White exterior | -0.289 | 0.677*** | 0.624*** | 0.558*** | 0.506*** |
| | (0.360) | (0.130) | (0.101) | (0.131) | (0.009) |
| Energy Star | 0.023 | 0.089 | 0.092 | 0.099 | 0.110*** |
| | (0.182) | (0.126) | (0.126) | (0.138) | (0.004) |
| Extra noise | 0.395* | 0.248** | 0.312** | 0.411** | 0.466*** |
| insulation | (0.207) | (0.125) | (0.120) | (0.162) | (0.010) |
| Number of special | 0.009 | 0.050 | 0.052 | 0.054 | 0.052*** |
| programs | (0.058) | (0.035) | (0.039) | (0.047) | (0.001) |
| Child lockout | -0.073 | 0.204 | 0.200 | 0.174 | 0.174*** |
| | (0.164) | (0.172) | (0.167) | (0.171) | (0.005) |
| Repair rate | -2.397 | 2.048 | 1.627 | 1.060 | 0.733*** |
| | (3.156) | (3.272) | (2.957) | (2.793) | (0.129) |
| Total advertising | -0.006 | 0.004 | 0.003 | 0.001 | 0.001*** |
| expenditure | (0.005) | (0.002) | (0.002) | (0.002) | (0.0002) |
| Retailer Best Buy | -0.097 | -1.045*** | -1.062*** | -1.085*** | -1.098*** |
| | (0.086) | (0.299) | (0.307) | (0.309) | (0.002) |
| Retailer H. H. Gregg | -0.369*** | -1.903*** | -1.963*** | -2.054*** | -2.103*** |
| | (0.119) | (0.282) | (0.299) | (0.278) | (0.008) |
| Retailer Home Depot | -0.162 | -0.738** | -0.765** | -0.804** | -0.826*** |
| | (0.106) | (0.314) | (0.321) | (0.324) | (0.004) |
| Retailer Lowe's | -0.180** | -0.301 | -0.334 | -0.375* | -0.401*** |
| | (0.091) | (0.230) | (0.231) | (0.224) | (0.004) |
| Retailer Sears | 0.015 | -0.436 | -0.435 | -0.430 | -0.427*** |
| | (0.113) | (0.442) | (0.445) | (0.445) | (0.001) |
| Brand FE | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| Brand time trends | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| Year FE | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| Observations | 1,590 | 1,590 | 1,586 | 1,590 | 1,590 |
| Kleibergen-Paap F-statistic | 22.979 | | | | |
| Avg. own-price elasticity | | | -0.964 | -2.416 | -3.258 |

Notes: Column (1) presents results for the first stage regression of prices on the real exchange rate. Column (2) includes reduced form estimates for the simple logit model. Column (3) reports demand estimates for the simple logit without instrumenting for price. Column (4) presents demand estimates for the simple logit model using the RER as an instrumental variable for price. Column (5) shows demand estimates for the full mixed logit model presented in Section 4 and using the RER as an instrumental variable for price. Standard errors are clustered at the brand level. The own-price elasticity of residual demand is computed at the product level and the average is calculated by weighting products according to their sales volume. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# V Appendix to Section 7: Details on the welfare effects

## V.A Entry algorithm

The pseudo-code in Algorithm 1 illustrates this portfolio choice algorithm described in Section 7.

**Algorithm 1:** Heuristic portfolio choice algorithm

```
adjust_B = 1;
J^* ← pre-merger portfolio of all firms;
while adjust_B = 1 do                    /* until no adjustment for any brand */
    adjust_B = 0;
    for b ∈ B do                                   /* iterate through brands */
        adjust_b = 1;
        while adjust_b = 1 do               /* until no adjustment for brand b */
            ΔE[Π_remove] = [];
            ΔE[Π_add] = [];
            for j ∈ J_b do                     /* iterate through active products */
                append(ΔE[Π_remove], E_e[Π_f(J_f^* − 1_b^j)]);
            end
            for j ∈ J̃_b do                   /* iterate through inactive products */
                append(ΔE[Π_add], E_e[Π_f(J_f^* 1_b^j)]);
            end
            if max(max(ΔE[Π_remove]), max(ΔE[Π_add])) > 0 then
                if max(ΔE[Π_remove]) > max(ΔE[Π_add]) then
                    k = findmax( ΔE[Π_remove] );
                    J_f^* ← J_f^* − 1_b^k;
                    adjust_B = 1;
                else
                    k = findmax( ΔE[Π_add] );
                    J_f^* ← J_f^* + 1_b^k;
                    adjust_B = 1;
                end
                adjust_b = 0;
            end
        end
    end
end
```

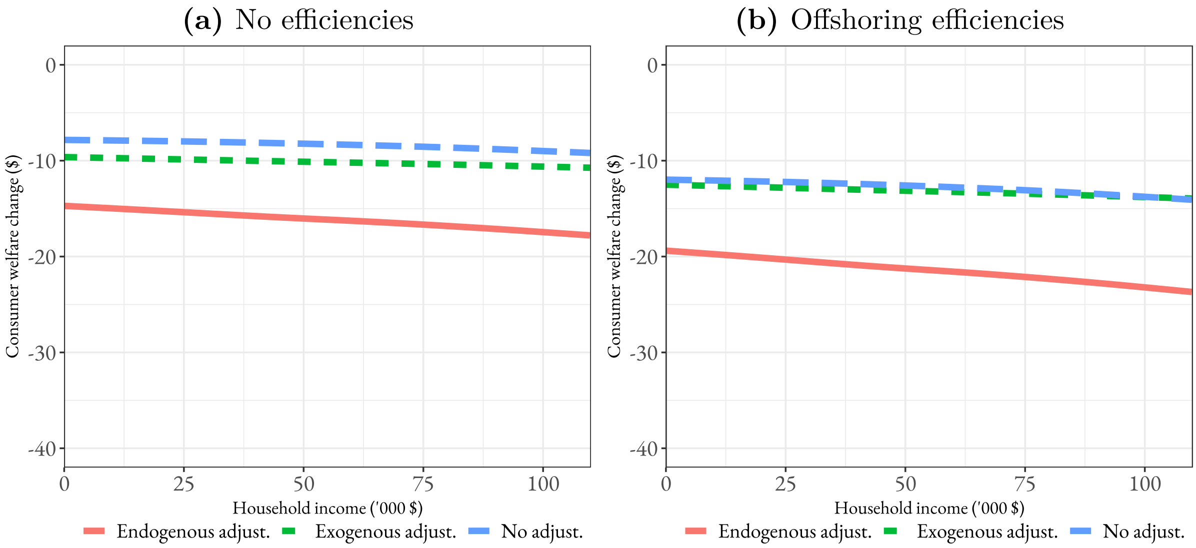
## V.B Detailed product market effects

# **Table A.9:** Product market effects of Maytag acquisitions by Haier and Whirlpool

| | **No portfolio adjustments** | | | | **Merger-independent adjustments** | | | | **Endogenous adjustments** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Efficiencies:* | **No efficiencies** | | **Offshoring** | | **No efficiencies** | | **Offshoring** | | **No efficiencies** | | **Offshoring** | |
| *Acquirer:* | Haier | Whirlpool | Haier | Whirlpool | Haier | Whirlpool | Haier | Whirlpool | Haier | Whirlpool | Haier | Whirlpool |
| *Prices* | | | | | | | | | | | | |
| Total industry | 0.0%<br>[-0.0%, 0.3%] | 2.7%<br>[1.7%, 3.7%] | -0.1%<br>[-2.0%, 0.1%] | 2.6%<br>[1.5%, 3.6%] | 0.1%<br>[0.0%, 0.2%] | 2.9%<br>[2.0%, 3.8%] | -0.9%<br>[-1.0%, -0.8%] | 2.7%<br>[1.8%, 3.6%] | [-0.9%, 1.1%] | [1.8%, 5.1%] | [-1.9%, 0.2%] | [1.7%, 4.9%] |
| Maytag | 0.0%<br>[-0.1%, 0.2%] | 5.8%<br>[2.8%, 8.8%] | -5.9%<br>[-10.8%, 1.0%] | 4.7%<br>[1.6%, 7.8%] | 0.0%<br>[-0.0%, 0.1%] | 8.8%<br>[5.6%, 12.0%] | -5.2%<br>[-5.3%, -5.1%] | 7.5%<br>[4.3%, 10.6%] | [-2.1%, 2.7%] | [3.6%, 11.5%] | [-6.2%, 1.6%] | [3.2%, 11.3%] |
| Whirlpool | 0.0%<br>[-0.0%, 0.0%] | 5.9%<br>[3.0%, 8.9%] | 0.0%<br>[-0.2%, 0.2%] | 6.2%<br>[3.2%, 9.2%] | 0.0%<br>[-0.0%, 0.0%] | 6.1%<br>[3.3%, 8.9%] | -0.2%<br>[-0.2%, -0.2%] | 6.1%<br>[3.2%, 8.9%] | [-3.0%, 3.0%] | [1.1%, 9.8%] | [-3.1%, 1.9%] | [1.0%, 10.0%] |
| *Consumer welfare* | | | | | | | | | | | | |
| All consumers | $-0.7M<br>[$-5M, $3M] | $-131M<br>[$-206M, $-55M] | $83M<br>[$12M, $155M] | $-116M<br>[$-191M, $-42M] | $-0.9M<br>[$-3M, $1M] | $-156M<br>[$-237M, $-75M] | $61M<br>[$59M, $63M] | $-140M<br>[$-221M, $-59M] | [$-32M, $33M] | [$-300M, $-197M] | [$58M, $152M] | [$-302M, $-197M] |
| | -0.0%<br>[-0.2%, 0.1%] | -4.9%<br>[-8.4%, -1.3%] | 3.1%<br>[0.3%, 5.9%] | -4.3%<br>[-7.8%, -0.9%] | -0.0%<br>[-0.0%, 0.0%] | -4.9%<br>[-8.0%, -1.8%] | 1.9%<br>[1.9%, 2.0%] | -4.4%<br>[-7.5%, -1.3%] | [-1.1%, 1.1%] | [-10.0%, -6.6%] | [1.9%, 5.2%] | [-10.1%, -6.6%] |
| *Variable profits* | | | | | | | | | | | | |
| Total industry | $0.8M<br>[$-2M, $4] | $66M<br>[$27M, $105M] | $14M<br>[$-38M, $65M] | $76M<br>[$31M, $120M] | $0.6M<br>[$-1M, $-2M] | $81M<br>[$41M, $121M] | $26M<br>[$24M, $27M] | $85M<br>[$46M, $125M] | [$-18M, $23M] | [$30M, $97M] | [$42M, $91M] | [$24M, $97M] |
| | 0.0%<br>[-0.1%, 0.2%] | 3.7%<br>[1.2%, 6.1%] | 0.8%<br>[-2.3%, 3.8%] | 4.2%<br>[1.5%, 6.9%] | 0.0%<br>[-0.0%, 0.1%] | 4.1%<br>[2.0%, 6.2%] | 1.3%<br>[1.2%, 1.4%] | 4.3%<br>[2.2%, 6.5%] | [-0.9%, 1.2%] | [1.5%, 4.9%] | [2.1%, 4.7%] | [1.2%, 4.9%] |
| Maytag + Whirlpool | $0.8M<br>[$-1M, $2M] | $15M<br>[$-23M, $54M] | $14M<br>[$-72M, $99M] | $33M<br>[$-11M, $77M] | $0.02M<br>[$-1M, $1M] | $18M<br>[$-18M, $54M] | $68M<br>[$67M, $68M] | $30M<br>[$-6M, $66M] | [$-29.1M, $35.3M] | [$-67M, $24M] | [$90M, $186M] | [$-69M, $21M] |
| | 0.1%<br>[-0.0%, 0.5%] | 1.7%<br>[-1.9%, 5.3%] | 3.2%<br>[-16.7%, 23.1%] | 3.7%<br>[-0.4%, 7.8%] | 0.0%<br>[-0.1%, 0.1%] | 1.8%<br>[-1.2%, 4.8%] | 17.6%<br>[17.5%, 17.7%] | 3.0%<br>[0.0%, 6.0%] | [-5.6%, 7.0%] | [-5.4%, 1.8%] | [15.9%, 38.8%] | [-5.5%, 1.6%] |
| *Total profits* | | | | | | | | | | | | |
| Total industry | $0.8M<br>[$-2M, $4] | $66M<br>[$27M, $105M] | $14M<br>[$-38M, $65M] | $76M<br>[$31M, $120M] | $0.6M<br>[$-1M, $-2M] | $81M<br>[$41M, $121M] | $26M<br>[$24M, $27M] | $85M<br>[$46M, $125M] | [$-19M, $19M] | [$76M, $133M] | [$18M, $74M] | [$78M, $132M] |
| | | | | | | | | | [-1.5%, 1.4%] | [5.6%, 10.3%] | [1.4%, 5.8%] | [5.8%, 10.2%] |
| Maytag + Whirlpool | $0.8M<br>[$-1M, $2M] | $15M<br>[$-23M, $54M] | $14M<br>[$-72M, $99M] | $33M<br>[$-11M, $77M] | $0.02M<br>[$-1M, $1M] | $18M<br>[$-18M, $54M] | $68M<br>[$67M, $68M] | $30M<br>[$-6M, $66M] | [$-5.8M, $6.4M] | [$19M, $47M] | [$91M, $119M] | [$20M, $48M] |
| | | | | | | | | | [-12.8%, 11.8%] | [2.3%, 6.3%] | [-92.5%, 189.4%] | [2.4%, 6.2%] |

Notes: The first four columns show the effects of a Whirlpool and Haier acquisition of Maytag without product portfolio adjustments. The next four columns show the same comparison for merger-independent portfolio adjustments and the final four columns for endogenous portfolio adjustments. Each adjustment scenario includes results without marginal cost efficiencies and with offshoring efficiencies. 95% confidence intervals for effects without product portfolio adjustments and with merger-independent portfolio adjustments are computed using 100 residual bootstrap draws. Confidence sets for the expected effects with endogenous portfolio adjustments are based on 50 fixed cost draws for each potential product from a uniform distribution, where the domain are the confidence sets of brand-level fixed costs, and 500 demand and supply residual draws. Maytag includes all products marketed under the brands owned by Maytag pre-acquisition (i.e. Admiral, Amana, Magic Chef and Maytag).

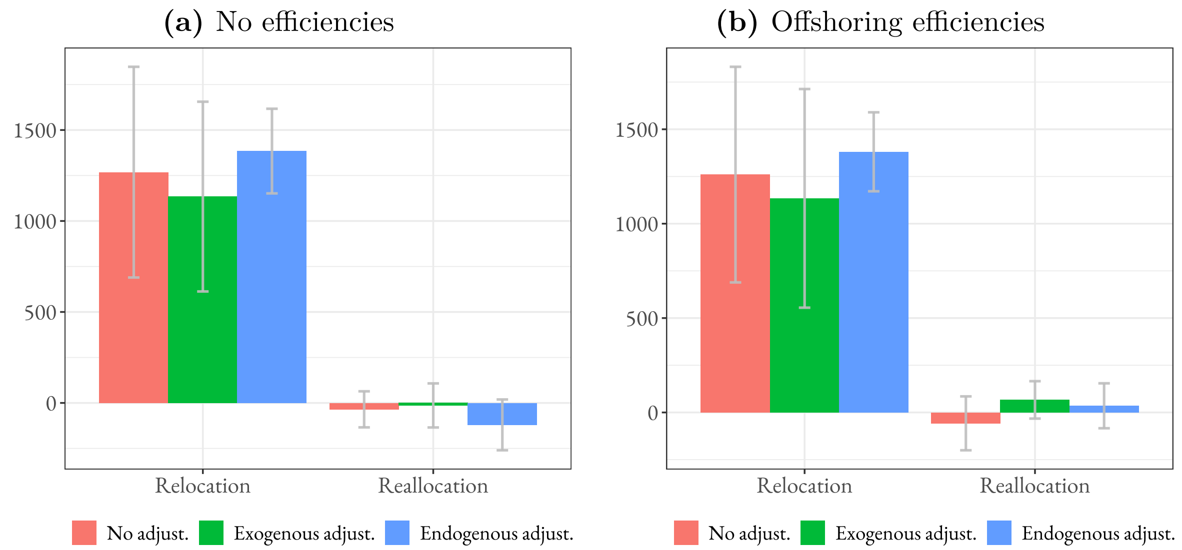
**Figure A.10:** Consumer welfare change by household income




Notes: Both graphs show the absolute change in consumer welfare between a Maytag acquisition by Whirlpool and Haier according to household income. The consumer welfare changes are shown for three adjustment scenarios: No product portfolio adjustments, exogenous adjustments, and fully endogenous adjustments. Simulations are based on $1,000$ household draws per market. For expositional simplicity, the graphs only show households with an annual income of less than 110,000$, covering 80% of drawn households. In the left panel, no marginal cost efficiencies are credited. In the right panel, offshoring efficiencies are credited to Maytag products.

## V.C Employment effect decomposition

**Figure A.11:** Decomposition of employment effects




Notes: The histograms decompose the employment effects in Table 10 into a relocation and a reallocation effect. The former is related to differences in U.S. employment between Maytag acquisitions by Whirlpool and Haier because of different plant relocation plants. The latter is related to differences in U.S. employment between the acquisitions due to different reallocations of market shares between the merging parties, competitors, and the outside good.

## V.D Estimating consumer welfare and employment effects for other household appliances

In this subsection, I outline a very rough estimation of the consumer welfare and employment effects of alternative Maytag acquisitions by Whirlpool vs. Haier for other household appliances. This exercise is based on very strong assumptions and rough approximations. The estimated magnitudes should therefore be interpreted with caution. The aim of this exercise is merely to provide an idea about the direction in which the offsetting job value would shift, had I incorporated all affected appliance categories in the estimation.

The first difficulty is to estimate the consumer welfare effects of the hypothetical acquisitions in other product categories. In a first step, I identify which product categories to consider.

Table A.10 reports volume shares by manufacturer pre-merger for all appliance categories where Maytag was active and overlapped with either Haier or Whirlpool.[60] The data is based on a consensus survey among market participants conducted by the industry journal *Appliance*. Since products are attributed to who manufactures a product, not who markets and sells it, there are some important discrepancies. In particular, products sold by Sears are manufactured by competitors. For example, all clothes washers marketed by Sears in 2005 were manufactured by Whirlpool.

[60]Maytag also sold floor care products, however, neither Haier, nor Whirlpool were active in that market.

**Table A.10:** Volume share by manufacturer from *Appliance* in 2005 (%)

| | Clothes dryers | Clothes washers | Dishwashers | Ranges | Refrigerators |
|---|---|---|---|---|---|
| Whirlpool | 56 | 51 | 34 | 19 | 25 |
| Maytag | 20 | 19 | 17 | 13 | 11 |
| General Electric | 13 | 17 | 25 | 45 | 29 |
| Electrolux | 9 | 9 | 18 | 16 | 25 |
| Bosch | | | 3 | | |
| Haier | | | | | 2 |
| Other | 2 | 4 | 3 | 4 | 8 |
| HHI | 3,769 | 3,348 | 2,412 | 2,762 | 2,281 |
| $\Delta$HHI | 2,191 | 1,938 | 1,156 | 467 | 550 |

Notes: The data is based on a consensus survey of market participants by the industry journal *Appliance*. Appliances are attributed to manufacturers, not brand owners, leading to discrepancies as compared to the *TraQline* data. For example, all clothes washers marketed by Sears are counted to Whirlpool, since they are manufactured by Whirlpool in 2005. Refrigerators only includes standard refrigerators and omits compact and built-in under-the-counter refrigerators. These constitute a different market.

As expected, market concentration and the overlap between Whirlpool and Maytag is largest for laundry products. The increase in the HHI after an acquisition by Whirlpool is around 2,000 for laundry products, 1,000 for dishwashers, and 500 for ranges and refrigerators. Haier and Maytag only overlap in the market for refrigerators, however, also there the overlap is unlikely to lead to any price effects.

To get a rough approximation of the loss in consumer welfare, I now make several strong assumptions. Since Nocke and Whinston (2020) show that emphasizing the change in HHI is more important for merger screening than the post-merger HHI, I focus on the increase in the HHI in what follows.

First, I assume that the percentage change in consumer welfare is proportional to the change in the HHI and that this relationship is the same across product categories. With endogenous portfolio adjustments and without efficiencies, the 95 percent confidence set of consumer welfare losses after a Whirlpool compared to a Haier acquisition for clothes washers ranges from 5.9 to 9.5 percent. Based on this, I assume that consumer welfare decreases between 6.7 and 10.4 percent for clothes dryers, 3.5 and 5.5 percent for dishwashers, 1.4 and 2.2 percent for ranges, and 1.7 and 2.6 percent for refrigerators.

Second, we need an estimate of pre-merger consumer welfare for each appliance category. I assume that pre-merger consumer welfare is proportional to the number of appliances of a particular appliance type sold in 2005. Based on the estimates from *Appliance*, there were 8.2 million clothes dryers, 9.2 million clothes washers, 7.4 million dishwashers, 10.0 million ranges, and 11.1 million standard sized refrigerators sold in 2005.

Taken together, I find a total decrease in consumer welfare of a Maytag acquisition by Whirlpool compared to Haier of between \$600 million (clothes washers: 194 million \$;

clothes dryers: \$195 million; dishwashers: \$93 million; ranges: \$51 million; refrigerators: \$67 million) and \$936 million (clothes washers: \$304 million; clothes dryers: \$303 million; dishwashers: \$146 million; ranges: \$79 million; refrigerators: \$104 million).

The second difficulty is to estimate the employment effects of the hypothetical acquisitions in other product categories. As seen for the analysis of clothes washers, employment effects stem from three sources: the relocation of Maytag production, the reallocation of inside good market shares between competitors, and changes in the overall share of the inside good (i.e. the market size). For simplicity, I only estimate the difference in the relocation effect on employment for other appliance products. Since the overlap for ranges and refrigerators is low, changes in employment due to the reallocation of market shares, as well as changes in the market size are going to be low. For clothes dryers and dishwashers, omitting these effects leads to an overestimate of the difference in employment effects between the acquisitions, since the reallocation to competitors producing abroad and the decrease in market size only occur after an acquisition by Whirlpool. The decomposition of employment effects for clothes washers showed, however, that these latter two effects are significantly smaller in magnitude compared to the relocation effect.

According to Maytag (2005), the company had 16,900 employees in its home appliance division, of which 85 percent worked in the United States. According to news reports, Whirlpool cut 4,500 U.S. jobs at Maytag plants after its acquisition and created 1,500 new U.S. jobs at existing Whirlpool plants. Haier is assumed to offshore all Maytag jobs after an acquisition. Thus, Haier would reduce U.S. appliance manufacturing by 11,365 additional jobs compared to an acquisition by Whirlpool.

The number of additional U.S. jobs cut at Maytag because of production relocation after a Haier acquisition in home appliance categories that are not clothes washers are thus the sum of 11,365 and the model prediction of Maytag clothes washer jobs relocated by Whirlpool post-merger. The 95 percent confidence set for the latter is between 495 and 829. Overall, the number of additional Maytag jobs relocated by Haier in other product categories is between 11,860 and 12,194.

Taking the estimated product market and employment effects together, this results in an offsetting job value of between \$49,139 and \$78,907 for all other household appliances.

**UniCredit Foundation**

Piazza Gae Aulenti, 3

UniCredit Tower A

20154 Milan

Italy

**Giannantonio De Roni** – *Secretary General*

e-mail: giannantonio.deroni@unicredit.eu

**Annalisa Aleati** - *Scientific Director*

e-mail: annalisa.aleati@unicredit.eu

Info at:

www.unicreditfoundation.org

UniCredit Foundation