Essays on pricing strategy and market effects of new product introduction

by

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AN ABSTRACT OF A DISSERTATION

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Abstract

This dissertation consists of two essays that analyze economic issues that fall within the sub-field of economics known as Industrial Organization. The essays focus on commercial aviation and coffee industries, respectively. The two essays maintain tight connections between economic theory and empirical analysis, and examine the observed economic phenomena in their respective markets in the past few years using econometric methods that are popular in Industrial Organization.

The first essay investigates the U.S. domestic airlines' pricing strategies in response to the significant worldwide decline in crude oil price beginning in mid-2014 through to 2015. Specifically, this essay examines the market mechanisms through which crude oil price may influence airfare, which facilitates identifying the possible market and airline-specific characteristics that may influence the extent to which crude oil price changes affect airfare. The essay first uses a simple theoretical model of air travel demand and Nash equilibrium price-setting behavior of airlines to derive clear theoretical predictions that guide proper specification of reduced-form regression models and help with interpreting empirical results. The empirical results reveal that there is a positive pass-through from changes in crude oil price to airfare, but the magnitude of the pass-through depends on several origin-destination market and airline-specific characteristics. In particular, the magnitude of the pass-through tends to be greater in more competitive origin-destination markets, smaller in longer distance markets, and smaller among airlines that purchase fuel using hedging contracts.

The second essay analyzes the market effects of the introduction of single-cup coffee brew technology on the U.S. brew-at-home coffee market, particularly on the traditional auto-drip brew coffee segment. The introduction of single-cup coffee brew technology in the late 2000s has not

only changed the way many brew-at-home coffee drinkers brew and consume coffee in daily life, i.e. a change from brewing one "pot" at a time to making one cup at a time, but also altered the overall landscape of the brew-at-home coffee market in the U.S. This paper analyses the economic impacts in the U.S. brew-at-home coffee market associated with the introduction and growing presence of single-cup coffee brew technology. We find that a typical coffee drinker is willing to pay up to 2.52 cents extra per fluid ounce to consume freshly brewed coffee from single-cup brewing machines instead of using the traditional auto-drip brewing method, and this marginal willingness to pay gap increases with consumers' income level. Second, we find that both the demand and profitability of traditional auto-drip brew coffee products are substantially lower owing to the growing consumer valuation of single-cup brew technology. Last, our analysis reveals that consumers enjoy substantially higher welfare owing to the introduction and growing popularity of single-cup brew coffee products.

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Major Professor
Philip G. Gayle

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Dedication

To my parents, without whom nothing is possible.

To my American family, for their unconditional love, care, and belief.

Chapter 1 - Cost Pass-Through in Commercial Aviation

1.1 Introduction

Brent Crude, the energy price index that many airline executives monitor, serves as an important instrument for these executives to predict future fuel costs for their airline because: (*i*) the index captures price movements of a key component of jet fuel; and (*ii*) the index is normally highly correlated with prices of its refinery products.[1] Crude oil price declined from $111.8/barrel in June 2014 to $38.01/barrel in December 2015, an approximate 66% reduction.[2] Consistent with the decline in crude oil price, financial information reported by the four major U.S. airlines, American, Delta, United, and Southwest, in their 10-K filings documented to U.S. Securities and Exchange Commission (SEC) shows that all four major airlines experienced a significant decline in their fuel expenses from 2014 to 2015 (see Table 1.1). For example, American and Delta Airlines reported more than 40% saving in fuel costs, while United and Southwest had over 30% reduction of fuel expenses during this period.[3] In spite of fuel cost savings, industry analysts have

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[1] The Financial Accounting Standards Board (FASB) Statement 133 requires a hedge must be shown to be highly effective to corporations. A hedge is deemed effective if the ratio of the change in value of the derivative (e.g. crude oil) to that of the hedged item (e.g. jet fuel) falls between 80% and 125%, i.e. "80/125 rule." Southwest (and many other air carriers) relies on crude oil and/or its refinery products to hedge against the risk of fuel costs fluctuations due to jet fuel price changes.

[2] Oil price is represented by Brent crude oil spot price from Energy Information Administration (EIA): https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=pet&s=rbrte&f=m.

[3] There are extensive studies that investigate the relationship between crude oil price and prices of its refinery petroleum products. For example, Asche et al (2003) applied multivariate analysis in oil industry in northern Europe and found evidence that prices of crude oil, gasoline and kerosene fuel are proportional with constant spreads. They further pointed out that refinery petroleum industry is an example of "supply driven market integration." Li (2010) also provided strong evidence that jet fuel price adjusts towards the long-run co-integration with crude oil price.

pointed out that airfares have been "essentially stable during this period."[4] Airline price data released by the Bureau of Labor and Statistics (BLS) showed that the monthly average airfare decreased by less than 5%,[5] which is quite trivial compared with the size of reduction in crude oil price as well as jet fuel price over this time period.

Table 1.1 Fuel Expense (% of Operating Expenses) for 4 Major U.S. Airlines

Year	American	Delta	United	Southwest
2013	35.4%	33.3%	34%	35.1%
2014	33.2%	35.4%	32%	32.3%
2015	21.6%	23%	23%	23%

	2014-2015 Fuel Expense % Change			
	- 41.2%	- 43.9%	- 36%	- 31.7%

Source: Airlines' SEC 10-K filings.

To obtain a better picture of how market airfare responded to crude oil and jet fuel prices during this time period, we plot the quarterly percentage change of crude oil price, jet fuel price and industry average airfare from the third quarter of 2013 to the fourth quarter of 2015 in Figure 1.1. In this price series plot, a notably positive relationship is evident between crude oil price and jet fuel price over the sample period. Notice that crude oil and jet fuel prices start to decline dramatically in mid-2014, whereas industry average airfare shows little or no co-movement with the energy prices during this period. This simple plot suggests that airline fuel cost savings have little or no pass-through to airfare. However, one may argue that an industry average airfare may not be reflective of how air carriers adjust airfare in response to their fuel cost changes. It is

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[4] The New York Times. http://www.nytimes.com/2016/02/07/business/energy-environment/airlines-reap-record-profits-and-passengers-get-peanuts.html?_r=0.

[5] BLS database URL source: http://data.bls.gov/timeseries/CUsR0000SETG01?output_view=pct_3mths.

possible that airfare tracks crude oil and jet fuel prices better in some air travel markets than others. To this end, we select two distinct markets:[6] OAK (Oakland, CA) to GEG (Spokane, WA) and SYR (Syracuse, NY) to PHX (Phoenix, AZ) and plot in the upper panel of Figure 1.2 the quarterly percentage change of crude oil price, jet fuel price, and average airfare in the two markets. Both markets are similar with respect to the number of airlines that compete in the market; specifically, each of the two markets has three competing airlines. However, the two markets differ substantially with respect to travel distance; in particular, OAK-GEG has a non-stop flight distance of 723 miles, while SYR-PHX has a non-stop flight distance of 2045 miles. In the upper panel of Figure 1.2, it is noticeable that changes in average fare in the OAK-GEG market intimately follow changes in energy prices. However, in the SYR-PHX market, changes in average fare often move in the opposite direction to changes in energy prices, and the opposite movement becomes more prominent from the third quarter of 2014 onwards. In summary, controlling for the number of competing carriers, the price change plots in the upper panel of Figure 1.2 suggest that fuel cost pass-through to airfare tends to be larger in the shorter distance market (OAK-GEG) compared to the longer distance market (SYR-PHX).

The lower panel of Figure 1.2 plots quarterly percentage changes in crude oil price, jet fuel price, and average airfare in two markets: OAK (Oakland, CA) to GEG (Spokane, WA) and BWI (Baltimore, MD) to MLB (Melbourne, FL). The BWI-MLB has a non-stop flight distance of 797 miles, which is comparable to the nonstop flight distance in the OAK-GEG market of 723 miles. However, BWI-MLB is a monopoly market served only by Delta Airlines with a one-stop connection flight, whereas OAK-GEG is a market served by three airlines offering multiple

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[6] The two markets are chosen to illustrate how airfare may respond differently to energy prices across markets with distinct characteristics.

competing products.[7] As such, it is reasonable to conjecture that the OAK-GEG market is more competitive than the BWI-MLB market. In the lower panel of Figure 1.2, while changes in average fare in the OAK-GEG market intimately follow the energy price changes, there is little or no co-movement of changes in airfare and changes in energy prices for the BWI-MLB market. In summary, controlling for market travel distance, the price change plots in the lower panel of Figure 1.2 suggest that fuel cost pass-through to airfare tends to be larger in the more competitive market (OAK-GEG) compared to the monopoly market (BWI-MLB).

Figure 1.1 Energy Prices and Average Airfare across all U.S. Domestic Air Travel Markets
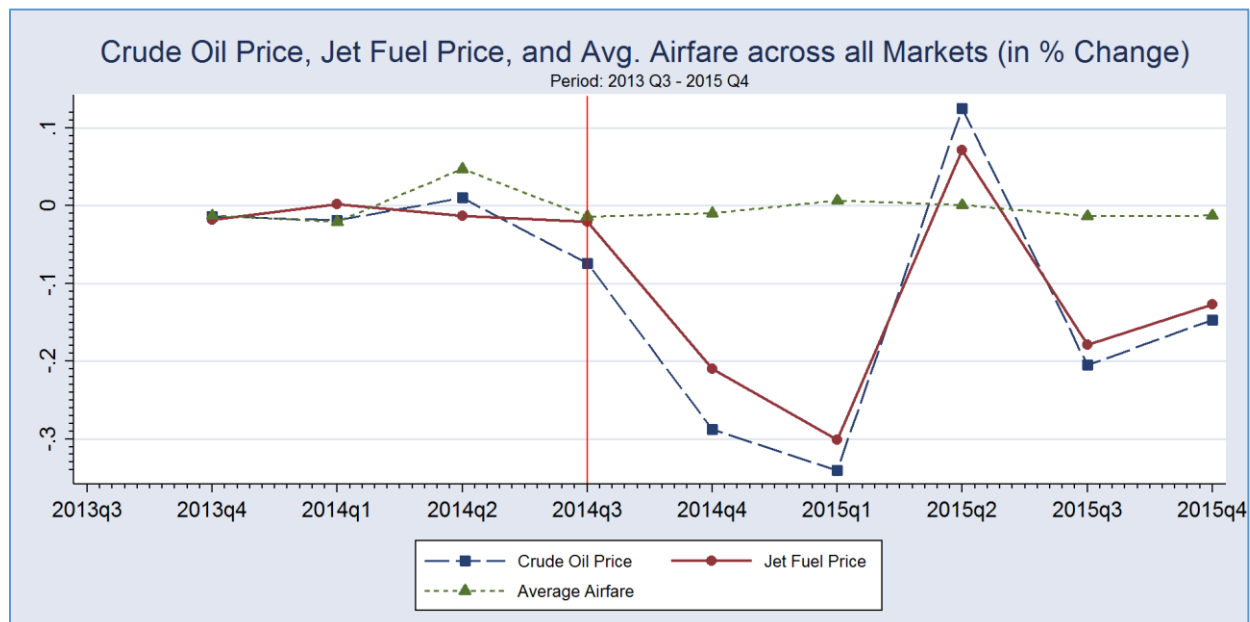
Source: DB1B database and Energy Information Administration (EIA)

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[7] In the OAK-GEG market, Delta and Alaska Airlines consistently provided one-stop connection flights, while Southwest Airlines consistently offered non-stop flights across the whole sample period. In the fourth quarter of 2013 and second quarter of 2014, Southwest exceptionally served two-stop connection flights together with a non-stop service.

Figure 1.2 Energy Prices and Airfare in select U.S. Domestic Air Travel Markets

Crude Oil Price, Jet Fuel Price, and Avg. Airfare in certain Markets (in % Change)
Period: 2013 Q3 - 2015 Q4

OAK-GEG (723 miles, N=3)
SYR-PHX (2045 miles, N=3)

Legend:
- Crude Oil Price
- Jet Fuel Price
- OAK-GEG (Oakland, CA-Spokane, WA, 723 miles, N=3)
- SYR-PHX (Syracuse, NY-Phoenix, AZ, 2045 miles, N=3)

Crude Oil Price, Jet Fuel Price, and Avg. Airfare in certain Markets (in % Change)
Period: 2013 Q3 - 2015 Q4

OAK-GEG (723 miles, N=3)
BWI-MLB (797 miles, N=1)

Legend:
- Crude Oil Price
- Jet Fuel Price
- OAK-GEG (Oakland, CA-Spokane, WA, 723 miles, N=3)
- BWI-MLB (Baltimore, MD-Melbourne, FL, 797 miles, N=1)

Source: DB1B database and Energy Information Administration (EIA)

The above observations raise two interesting questions that this paper seeks to answer: (*i*) what are the market mechanisms through which crude oil price influences airfare? and (*ii*) what are the possible factors that may influence the extent to which crude oil price changes affect airfare? To achieve this goal, we first specify a simple theoretical model of air travel demand and

supply in an origin-destination market. We rely on this simple theoretical model to study market channels through which changes in crude oil price may be reflected in airfare. The simple theoretical model yields clear predictions of the relationship between crude oil price and airfare, as well as reveals factors that may influence the strength of the relationship. With the theoretical model as a guiding framework, we subsequently compile a data set of information drawn from U.S. domestic air travel markets, then use reduced-form regression analysis to empirically test predictions from the theoretical model.

Key results from the analysis are as follows. First, our theoretical model predicts that there is a positive pass-through (also referred as "price transmission[8]") from crude oil price changes to airfare and the magnitude of this effect, i.e. the "pass-through rate," depends on several market characteristics. One such market characteristic is the extent of market competition among air carriers. Our theoretical model predicts that the size of pass-through becomes larger when markets are more competitive. Another market characteristic that also plays a role in affecting the size of pass-through is the distance between origin and destination. Consistent with what our theoretical model predicts, our empirical results reveal that there is a systematic positive marginal effect of crude oil price on airfare in U.S. domestic air travel markets. Furthermore, the magnitude of the pass-through rate depends on the competitiveness of the relevant U.S. domestic air travel market. In particular, the pass-through rate tends to be greater in more competitive markets. The empirical results also suggest that the pass-through rate is smaller in longer distance markets.

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[8] This term "price transmission" has been used interchangeably with "cost pass-through" in many empirical works that study the cost-price pass-through relationship in a variety of markets, such as Azzam (1999), Gomez and Koerner (2002), Aguiar and Santana (2002), Krivonos (2004), Frey and Manera (2005), Leibtag et. al. (2007), Bonnet and Villas-Boas (2016) and many others. However, these studies focus on the asymmetric patterns of cost-price pass-through in their markets of interest, which is not the focus in this paper.

The paper proceeds as follows. In the next section, we briefly review the relevant literature. In section 3 we specify and analyze a simple theoretical model of air travel demand and supply in an origin-destination market. Section 4 provides the empirical analysis, which starts by describing the data, then specifying and estimating the empirical model, and discussing the empirical results. Concluding remarks are gathered in section 5.

1.2 Related Literature

Empirical studies that focus on the cost-price pass-through relationship have been done on various industries. In the energy sector, Alexeeva-Talebi (2011) examines the impact of introducing the EU Emissions Trading Scheme (ETS) on the unleaded petrol retail prices in 14 EU Member States. In the retail food industry, Berck et al (2009) studies the pass-through from price shocks of certain raw commodities (corn, wheat, and gasoline) to supermarket retail prices of ready-to-eat cereals and fresh chicken. Kim and Cotterill (2008) estimates the pass-through rate of increases in milk prices to cheese prices. Bonnet and Villas-Boas (2016) focus on the French coffee market and studies the asymmetric pass-through patterns of retail coffee prices in response to upstream cost shocks. In the automobile industry, Gron and Swenson (2000) investigates how exchange rate changes influence the manufacturers' input market decisions and the importance of accounting for this impact on the estimated pass-through rate as a result of exchange rate changes. Hellerstein and Villas-Boas (2010) studies the relationship between a firm's degree of vertical integration along the supply chain and its pass-through of exchange-rate-induced cost shocks to the retail prices in the U.S. auto industry.

In the airline industry, airline cost structure has been well explored by a considerable number of studies.[9] However, there has been a scarcity of studies that focus on the cost-price pass-through relationship. A subset of these studies on the airline industry is purely theoretical analysis that examines the impact of cost-side shocks on airfare, product quality, airline performance, and other market outcome variables. Forsyth (2008) studies the impact of climate change policies, such as carbon taxes or carbon emission permits (referred to as an increase in "effective price of fuel"[10]) on competition, airfare, and profitability. The author found that the impact differs by market structure. The relevant metric of market structure being whether the airline city-pair market is competitive, monopolistic or oligopolistic. The author also argues that airlines are unlikely to be able to pass on the full cost change to airfare in the short run, though in the long run, it is likely that airlines will exit from some city pairs, and this will enable the remaining airlines to raise their fares and restore their profitability. Using a theoretical model, Brueckner and Zhang (2010) examine the effect of airline emission charges on airfare, airline service quality, and network structure. They find that an increase in spot market fuel prices, or an equivalent imposition of

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[9] Hirsch (2006) and Neven, Roller, and Zhang (2006) focus on airline labor input and show that labor cost should be endogenous to airline profits as airlines and unions both exhibit some bargaining power in terms of airline workers wage level. Ryerson and Hansen (2013) examine how jet fuel price influences aircraft operating costs using two types of operating cost models and find that fuel price plays a large role in airlines' decision on choosing the optimal aircraft size in order to minimize operating cost per seat mile. Windle (1991), Zuidberg (2014) and Bitzan and Peoples (2016) also find the positive impact of jet fuel price on airline operating cost.

[10] Many studies that are conducted with respect to the economic effects of the introduction of European Emission Trading Scheme in the aviation sector adopt the similar idea, i.e. either increasing spot market jet fuel prices, a carbon-tax scheme or carbon emission permits charge is effectively viewed as equivalent to an increase in jet fuel prices paid by airlines. These studies include but are not limited to Forsyth (2008), Brueckner and Zhang (2010), Toru (2011), Malina et al. (2012), Brueckner and Abreu (2016).

airline emission charges, will lead to a higher airfare, lower flight frequency, higher load factor, and more fuel-efficient aircrafts.

Empirical studies such as Malina et al. (2012), evaluate the economic impact of the European Emission Trading Scheme (ETS) on U.S. airlines. They find the impact to be relatively small. The rationale posited is that U.S. airlines may not pass through to airfare the full cost of emission charge since the imperfectly competitive market structure facilitates airlines with market power to absorb part of the cost increase. Koopmans and Lieshout (2016) attempt to identify the most likely pass-through rates for aviation markets for different countries based on previous theoretical findings of the pass-through rate in various market settings.[11] They compute concentration level (measured by Herfindahl-Hirschman Index) for each aviation market and suggest that most aviation markets in the world can be characterized as an oligopoly with differentiated products. Based on the pass-through rates in differentiated oligopolies computed by Zimmerman and Carlson (2010), Koopmans and Lieshout (2016) further suggest that an airline-specific cost shock is likely to have a less than 50 percent pass-through to airfare, but an industry-wide cost shock will have a larger pass-through to airfare depending on the degree of competition between airlines.

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[11] Bulow and Pfleiderer (1983) compute the pass-through rates in a perfect competitive environment and in monopolistic market. They find that an industry-wide cost change will be completely passed along to consumers in a perfect competitive market. A monopolist with a constant marginal cost will pass through 50 percent of a marginal cost change to market price when facing a linear demand. Zimmerman and Carlson (2010) focus on analyzing the role of product differentiation on firm-specific and industry-wide pass-through rates. They find disparate pass-through across the Cournot and Bertrand models. In differentiated oligopoly markets with Cournot type, firm-specific pass-through rates are between 20 percent and 50 percent and sector-wide pass-through rates are greater than the above range. Whereas in Bertrand type market structure, firm-specific pass-through rates are less than 50 percent while greater than 50 percent for sector-wide cost shocks.

Duplantis (2011) examines conditions under which airline fuel costs are passed on to consumers and estimates the respective fuel cost pass-through rates under these conditions. The author uses reduced-form regression analysis and finds an industry-wide fuel pass-through rate of 0.08 during periods of constant capacity, and 0.89 during periods of changing capacity. This finding is somewhat in line with the argument made by Borenstein and Rose (2007) that fuel cost is relatively fixed unless the airline can quickly adjust capacity with fuel price changes. Toru (2011) studies how airlines fuel cost increase triggered by increasing jet fuel price and environmental policy change is passed through to airfare in the EU airline market and its impact on air traffic, airline profits and consumer welfare. Specifically, the author uses a structural econometric model with standard logit demand and Bertrand-type market competition to compute the pass-through rates under counterfactual experiments with increases in "effective jet fuel price". The average estimated pass-through rates under these simulations fall into the range of 0.985 to 0.989 when the corresponding jet fuel price or an equivalent emission charge increase by 50% to 500%. The author suggests that the European airline market is highly competitive and that airlines are able to pass most of the fuel cost changes to passengers. This result to some extent is close to the finding in PWC (2005), which finds aviation fuel pass-through rates of 90% for low-cost carriers and 105% for full-service carriers.[12]

Our paper is different from the above studies in the following ways. First, unlike previous studies, we consider both demand-side and supply-side market channels through which changes in crude oil price pass-through to airfare. For example, on the air travel demand side, changes in crude oil price, through the pressure placed on gasoline price, trigger changes in consumer substitution between air travel and private automobile travel in shorter distance markets. On the

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[12] The results suggest that it takes up to two years for the full pass-through impact to become apparent. (Page 43)

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air travel supply side, changes in crude oil price spur changes in jet fuel price, which in turn causes airline fuel costs to change. However, it is important to note that the demand-driven price transmission channel considered in our analysis has not been considered in the aforementioned literature.[13] Second, unlike previous studies our empirical model allows airline-specific characteristics to affect market airfare level as well as the rate of cost pass-through. Particularly, we consider the role that airline jet fuel hedging decisions may play in influencing the size of fuel cost pass-through.[14]

1.3 Theoretical Model

The purpose of this section is to provide a simple theoretical framework to describe market mechanisms through which changes in crude oil price pass through to airfare, as well as to reveal and better understand some underlying factors that may play a role in influencing the size of pass-through. The theoretical model comprises both demand and supply sides of the market for air travel.

To construct our consumer demand function, we consider the potential substitution between air travel and private automobile travel, which depends on the market distance between origin and destination. In line with the argument made by Hayashi and Trapani (1987), the substitutability between flying and driving is influenced by the relevant ground transport cost,

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[13] We find one exception by Hayashi and Trapani (1987) who explicitly model the role of energy costs in affecting both demand and supply side of US air travel market.

[14] Carter, Rogers and Simkins (2004), find that jet fuel hedging is positively related to airline firm value, and "hedging premium" constitutes approximately 12-16% increase in firm value.

determined by gasoline price and time spent driving.[15] Following the argument made by Hayashi and Trapani (1987), air travel as well as other modes of mass transit, become relatively cheaper compared with private automobile travel when there is an increase in gasoline price. Therefore, we introduce gasoline price into the air travel demand equation. In terms of air travel supply, we consider airline fuel cost as a major component of airline operating costs, and therefore it is directly affected by jet fuel price. Due to the fact that both gasoline and jet fuel are petroleum products that are refined from crude oil,[16] changes in their prices are driven by changes in crude oil price.

In summary, our discussion above posits that changes in crude oil price affect both the demand and supply sides of air travel markets. In particular, we posit that crude oil price changes affect the demand for air travel via influencing the relative cost of automobile travel through causal changes in gasoline price, while the supply side of air travel is affected due to causal changes in jet fuel price. Consistent with these arguments, Figure 1.3 and Figure 1.4 show that crude oil, gasoline, and jet fuel prices are positively correlated.

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[15] Hayashi and Trapani (1987) consider the total ground transport cost of a trip is the sum of gasoline consumption valued at current cost per gallon, and time cost valued at average hourly earnings of non-supervisory personnel for all industries in the US. However, to simply the analysis in our model, we do not explicitly model the time spent on driving.

[16] http://www.eia.gov/energyexplained/index.cfm?page=oil_refining.

Figure 1.3 Energy Prices in Dollar Value

Crude Oil Price, Jet Fuel Price, and Gasoline Price (in dollar)
Period: 2013 Q3 - 2015 Q4
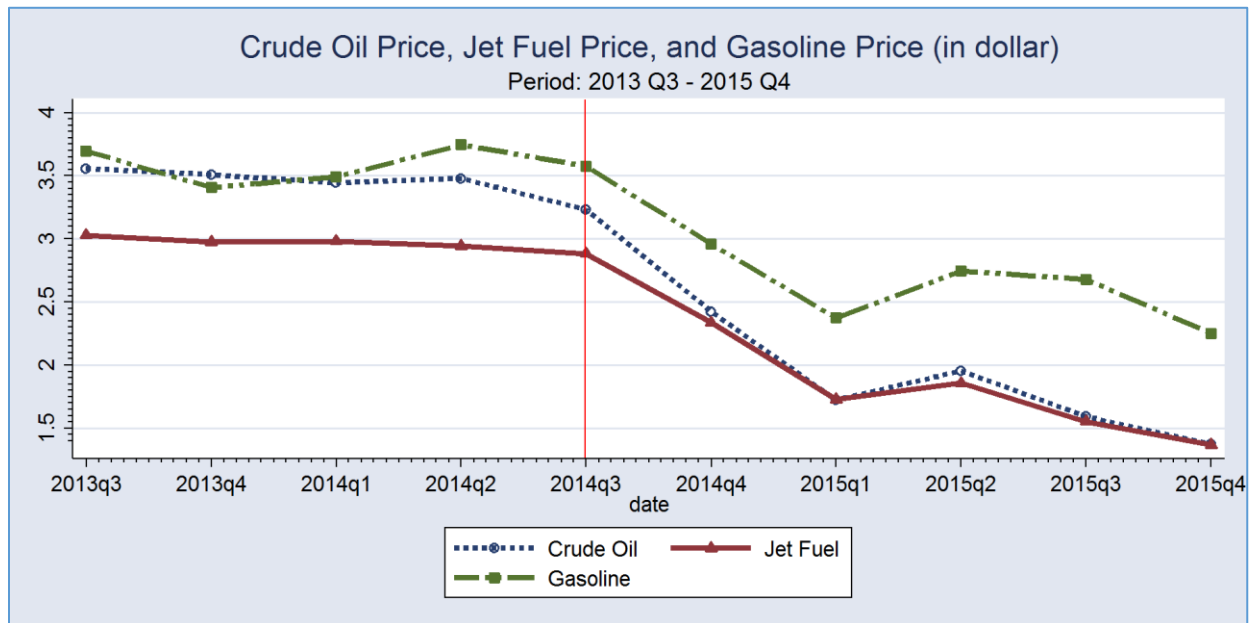
Source: Energy Information Administration (EIA)

Figure 1.4 Energy Prices in Percentage Change

Crude Oil Price, Jet Fuel Price, and Gasoline Price (in % Change)
Period: 2013 Q3 - 2015 Q4
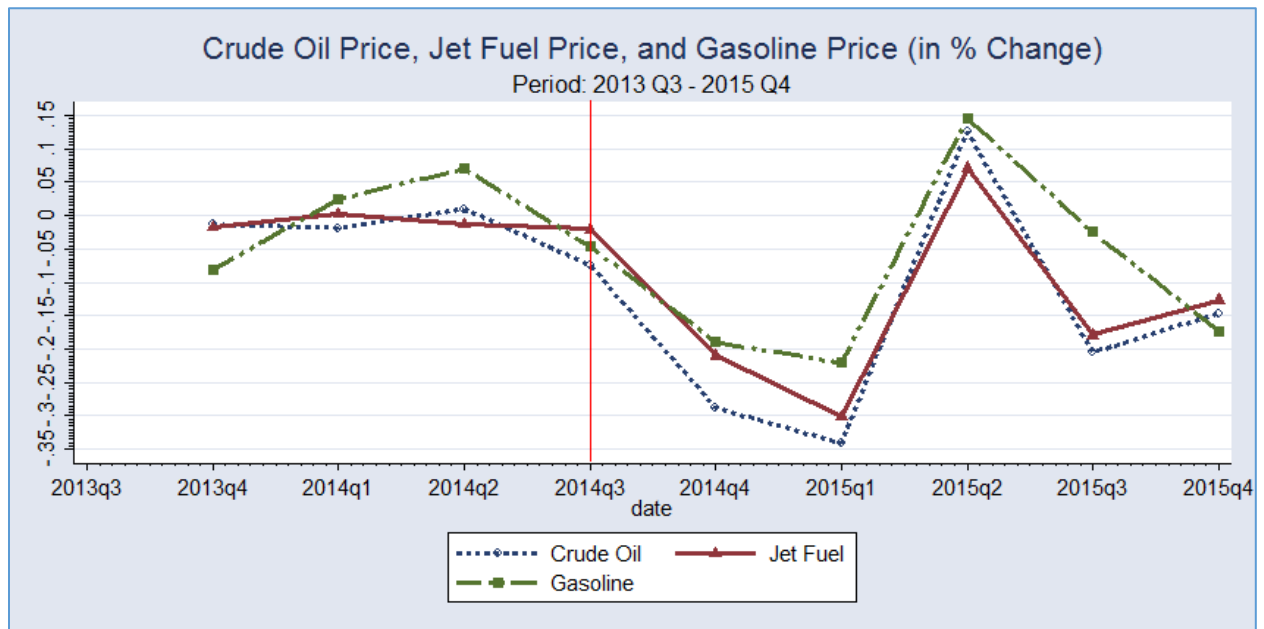
Source: Energy Information Administration (EIA)

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1.3.1 Demand

We think of an air travel market as directional travel between a specific origin and destination, while an air travel product is the specific routing used when transporting passengers from the origin to destination. As such, a given origin-destination market may have several competing products that are differentiated by their routing.

Following from Shubik-Levitan demand,[17] air travel demand among n differentiated air travel products in a market can be represented by the following system of equations:

$$\begin{pmatrix} q_1 = H - \beta P_1 + \tilde{\beta}(P_2 + P_3 + \cdots + P_n) \\ q_2 = H - \beta P_2 + \tilde{\beta}(P_1 + P_3 + \cdots + P_n) \\ \vdots \\ q_n = H - \beta P_n + \tilde{\beta}(P_1 + P_2 + \cdots + P_{n-1}) \end{pmatrix} \tag{1.1}$$

which can be written more compactly as:

$$q_i = H - \beta P_i + \tilde{\beta} \sum_{j \neq i}^{n-1} P_j \quad \text{for all } i = 1, 2, \dots, n \tag{1.2}$$

where

$$H = h_0 + h_1 X + \gamma P_g \tag{1.3}$$

$$\gamma = e^{-\gamma_0 dist} \tag{1.4}$$

$$\beta = e^{-\beta_0 dist} \tag{1.5}$$

$$P_g = \delta_0 + \delta_1 P_c \tag{1.6}$$

In the equations above, q_i represents the demand level for air travel product i, and P_i is the associated price level for product i, where $i = 1, 2, \dots, n$. All other products are considered to be substitute goods to product i, placing an equal weight of impact on product i's demand, which is measured by parameter $\tilde{\beta} > 0$; X is a vector of variables that influence the level of air travel demand, while h_1 is a vector of parameters that capture the marginal demand impact of each of

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[17] A demand system outlined and discussed in Shubik and Levitan (1980).

the variables in X, respectively; P_g and P_c represent gasoline price and crude oil price respectively; while $dist$ is a metric of market distance, measured by the non-stop flying distance between the origin and destination of the market.

As discussed previously, it is expected that consumers' preference between private automobile travel and air travel depends on the relative cost between the two modes of transportation. We use non-stop flying miles between the market's endpoints as an index of the market distance. The assumption is that this metric of market distance is positively correlated with driving distance. We also assume that the cost to the consumer of automobile travel, which includes the opportunity cost of time, increases faster with market distance compared to the cost to the consumer of air travel. As such, at any given gasoline price and jet fuel price, the cost to the consumer of flying relative to driving decreases with market distance. To capture these ideas in the system of air travel demand equations, we assume that γ, which measures the direct marginal effect of gasoline price on air travel demand, is positive and a decreasing function of market distance since parameter $\gamma_0 > 0$. Through parameter $\delta_1 > 0$, the positive marginal effect of gasoline price on air travel demand is translated into an indirect positive marginal effect of crude oil price on air travel demand.

Therefore, the system of demand equations is specified to capture the fact that automobile travel is normally considered as a closer substitute to air travel at relatively shorter travel distances.[18] Following this rationale, it is likely that gasoline price tends to have a larger impact on the air travel demand in short-haul markets. That is, changes in gasoline price should more heavily influence consumers' choice between driving and flying in markets with relatively shorter

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[18] Berry, Carnall and Spiller (1996, Page 13) also make similar arguments.

travel distances. However, as the market distance becomes relatively longer, travelers are less likely to switch from flying to driving. In this case, gasoline price changes may have a smaller impact on consumers' air travel demand, perhaps largely driven by the high opportunity cost of time associated with long-distance travel by driving. It then can be inferred that the crude oil price changes affect short-haul market demand relatively more intensively than longer distance market demand given the linkage between gasoline price and crude oil price ($\delta_1 > 0$).

Suggested by Gillen et al (2003), to account for the different elasticity of air travel demand in markets of differing distances, we consider the argument that travelers are likely to be more (less) sensitive to airfare changes in shorter (longer) distance markets. That is, air travel demand tends to be more elastic in shorter-haul markets than it is in longer-haul markets, simply because driving is often considered to be a more realistic alternative in relative shorter distance travel. We capture this effect by specifying β to be a decreasing function of market distance based on an exponential functional form with $\beta_0 > 0$. It is easier to see the relationship between market distance and the elasticity of air travel demand through the following inverse demand functions.

$$P_i = \frac{H}{\beta} - \frac{1}{\beta} q_i + \frac{\tilde{\beta}}{\beta} \sum_{j \neq i}^{n} P_j \qquad \text{for all } i = 1, 2, \dots, n \qquad (1.7)$$

Given the above inverse air travel demand equation, as well as the relationship between β and distance specified in equation (5), it is evident that β gets smaller as market distance increases, and smaller β corresponds to a steeper inverse demand curve, suggesting that demand is less elastic in longer distance markets.

We make a standard assumption when specifying a system of demand equations, which is that the demand impact of own price changes is greater than cross-price demand impacts, i.e. $\beta > \tilde{\beta}$, suggesting that own price elasticity is greater than cross-price elasticity for a given price level.

1.3.2 Supply Relation: Bertrand – Nash Pricing Game

We assume each of the n differentiated air travel products is offered by a different airline. As such, the system of n profit functions across competing airlines in the origin-destination market is the following:

$$\begin{pmatrix} \pi_1=(P_1-c_1)[H-\beta P_1+\tilde{\beta}(P_2+P_3+\cdots+P_n)] \\ \pi_2=(P_2-c_2)[H-\beta P_2+\tilde{\beta}(P_1+P_3+\cdots+P_n)] \\ \vdots \\ \pi_n=(P_n-c_n)[H-\beta P_n+\tilde{\beta}(P_1+P_2+\cdots+P_{n-1})] \end{pmatrix} \tag{1.8}$$

where $c_1, c_2, \ldots, c_n$ are the marginal costs firms incur to provide products $1, 2, \ldots, n$, respectively. We assume that airlines simultaneously and non-cooperatively choose prices, Bertrand-Nash fashion, to maximize profit. The set of prices in a Nash equilibrium must satisfy the following first-order conditions:

$$B \times \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_n \end{bmatrix} - \begin{bmatrix} H+\beta c_1 \\ H+\beta c_2 \\ \vdots \\ H+\beta c_n \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{1.9}$$

Where

$$B = \begin{bmatrix} 2\beta & -\tilde{\beta} & \cdots & -\tilde{\beta} \\ -\tilde{\beta} & 2\beta & \cdots & -\tilde{\beta} \\ \vdots & \vdots & \ddots & \vdots \\ -\tilde{\beta} & -\tilde{\beta} & \cdots & 2\beta \end{bmatrix} \tag{1.10}$$

Following the approach described in Wang and Zhao (2007), let $B = \frac{1}{a}[I - bT]$, where $a = \frac{1}{2\beta+\tilde{\beta}}$, $b = a\tilde{\beta} = \frac{\tilde{\beta}}{2\beta+\tilde{\beta}}$, I is an $n \times n$ identity matrix, and T is an $n \times n$ matrix of ones. The inverse of matrix B is given by:

$$B^{-1} = a\left[I + \frac{b}{1-nb}T\right] \tag{1.11}$$

We focus on a Nash Equilibrium in which products have strictly positive prices ($P_i > 0$) and production levels ($q_i > 0$). The system of first-order conditions yields the following expression for Nash equilibrium price levels:

$$\begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_n \end{bmatrix} = B^{-1} \begin{bmatrix} H + \beta c_1 \\ H + \beta c_2 \\ \vdots \\ H + \beta c_n \end{bmatrix} = \begin{bmatrix} a + \frac{ab}{1-nb} & \frac{ab}{1-nb} & \cdots & \frac{ab}{1-nb} \\ \frac{ab}{1-nb} & a + \frac{ab}{1-nb} & \cdots & \frac{ab}{1-nb} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{ab}{1-nb} & \frac{ab}{1-nb} & \cdots & a + \frac{ab}{1-nb} \end{bmatrix} \begin{bmatrix} H + \beta c_1 \\ H + \beta c_2 \\ \vdots \\ H + \beta c_n \end{bmatrix} \tag{1.12}$$

For any airline i, the optimal airfare P_i is:

$$P_i = \left(a + \frac{nab}{1-nb}\right) H + \left(a\beta + \frac{ab\beta}{1-nb}\right) c_i + \left(\frac{ab\beta}{1-nb}\right) \sum_{j \neq i}^{n-1} c_j \text{ ; for } i = 1,2,\dots,n \tag{1.13}$$

After substituting for a and b in equation (13), we obtain:

$$P_i = \frac{H}{2\beta - (n-1)\tilde{\beta}} + \frac{\beta[2\beta - (n-2)\tilde{\beta}]}{(2\beta + \tilde{\beta})[2\beta - (n-1)\tilde{\beta}]} c_i + \frac{\tilde{\beta}\beta}{(2\beta + \tilde{\beta})[2\beta - (n-1)\tilde{\beta}]} \sum_{j \neq i}^{n-1} c_j \tag{1.14}$$

The assumption of strictly positive prices and quantities implies that $2\beta - (n-1)\tilde{\beta} > 0$ for any given number of firms, n, where n=1, 2, ... Implications of the assumption of strictly positive prices and quantities are summarized in Lemma 1 (see Appendix for the proof).

Lemma 1: *Assume positive prices and quantities for each firm i=1,2,...,n in Nash Equilibrium, the following conditions must hold simultaneously:*

$$\begin{cases} P_i^* > 0 \\ q_i^* > 0 \\ c_i > 0 \\ H > 0 \\ \beta > \tilde{\beta} > 0 \end{cases} \equiv \begin{cases} 2\beta - (n-1)\tilde{\beta} > 0 \\ (2\beta + \tilde{\beta})H + \beta[2\beta - (n-1)\tilde{\beta}]c_i + \beta\tilde{\beta}\left(\sum_{j=1}^{n} c_j\right) > 0 \\ (2\beta + \tilde{\beta})H - (\beta + \tilde{\beta})[2\beta - (n-1)\tilde{\beta}]c_i + \beta\tilde{\beta}\left(\sum_{j=1}^{n} c_j\right) > 0 \\ c_i > 0 \\ H > 0 \\ \beta > \tilde{\beta} > 0 \end{cases}$$

We specify airlines' marginal cost functions as:

$$\begin{pmatrix} c_1 = \alpha_0 + \alpha_{11}P_f + \alpha_2 Z \\ c_2 = \alpha_0 + \alpha_{12}P_f + \alpha_2 Z \\ \vdots \\ c_n = \alpha_0 + \alpha_{1n}P_f + \alpha_2 Z \end{pmatrix} \tag{1.15}$$

which can be written more compactly as:

$$c_i = \alpha_0 + \alpha_{1i}P_f + \alpha_2 Z \quad \text{for all } i = 1,2,\dots,n \tag{1.16}$$

where

$$P_f = \phi_0 + \phi_1 P_c \tag{1.17}$$

In the equations above, c_i represents the marginal cost of air travel product $i = 1,2,\dots,n$; Z is a vector of cost-shifting variables that affect an airline's marginal cost; and P_f represents jet fuel price. We assume the parameter $\alpha_{1i} > 0$, which captures the direct positive marginal effect of jet fuel price on an airline's marginal cost; and through the assumption that parameter $\phi_1 > 0$, this effect translates into the indirect positive marginal effect of crude oil price on an airline's marginal cost.

Substituting equations (16) and (17) into the solution equation (equation (14)) for Nash equilibrium price yields the following reduced-form equation for Nash equilibrium price for air travel product $i = 1,2,\dots,n$:

$$P_i^*(\boldsymbol{\theta}; \boldsymbol{P_c}, \boldsymbol{dist}, \boldsymbol{X}, \boldsymbol{Z}) = H_0 + \frac{h_1}{2e^{-\beta_0 dist} - (n-1)\tilde{\beta}} X + \frac{e^{-\beta_0 dist}\alpha_2}{2e^{-\beta_0 dist} - (n-1)\tilde{\beta}} Z$$

$$+ \frac{\delta_0 + \delta_1 P_c}{2e^{-\beta_0 dist} - (n-1)\tilde{\beta}} e^{-\gamma_0 dist}$$

$$+ \frac{e^{-\beta_0 dist}\left[2e^{-\beta_0 dist} - (n-2)\tilde{\beta}\right]\alpha_{1i} + \tilde{\beta}e^{-\beta_0 dist}\left(\sum_{j \neq i}^{n-1} \alpha_{1j}\right)}{\left(2e^{-\beta_0 dist} + \tilde{\beta}\right)\left[2e^{-\beta_0 dist} - (n-1)\tilde{\beta}\right]} \phi_1 P_c \tag{1.18}$$

where

$$H_0 = \frac{h_0}{2e^{-\beta_0 dist} - (n-1)\tilde{\beta}} + \frac{\alpha_0 e^{-\beta_0 dist}}{2e^{-\beta_0 dist} - (n-1)\tilde{\beta}}$$

$$+ \frac{e^{-\beta_0 dist}\left[2e^{-\beta_0 dist} - (n-2)\tilde{\beta}\right]\alpha_{1i} + \tilde{\beta}e^{-\beta_0 dist}\left(\sum_{j \neq i}^{n-1} \alpha_{1j}\right)}{\left(2e^{-\beta_0 dist} + \tilde{\beta}\right)\left[2e^{-\beta_0 dist} - (n-1)\tilde{\beta}\right]} \phi_0 \tag{1.19}$$

$$\theta \equiv \left\{\beta_0, \tilde{\beta}, h_0, h_1, \gamma_0, \alpha_0, \alpha_{1i}, \alpha_{1j}, \alpha_2, \delta_0, \delta_1, \phi_0, \phi_1\right\} \tag{1.20}$$

The expression above that characterizes the Nash equilibrium price level reveals that airline i's optimal airfare in a given origin-destination market is determined by:

(i) X, Z: vectors of demand-shifting and cost-shifting variables, respectively;

(ii) $dist$: market distance measured by non-stop flying miles between the origin and destination;

(iii) P_c: the level of crude oil price, which influences airfare through air travel demand and supply channels.

(iv) H_0: a component that comprises a composite of demand and cost factors that determine the mean level of airline i's fare when the variables described in (i) through (iii) above are counterfactually set equal to zero.

1.3.3 Theoretical Analysis

1.3.3.1 The impact of crude oil price on airfare

The marginal effect of crude oil price on a typical airline's price level determines the cost pass-through relationship, or price transmission, from changes in crude oil price to changes in airfare. As such, the cost pass-through relationship is derived from our theoretical model based on the following partial derivative:

$$\frac{\partial P_i^*}{\partial P_c} = \underbrace{\frac{e^{-\gamma_0 dist}\delta_1}{2e^{-\beta_0 dist}-(n-1)\widetilde{\beta}}}_{Demand\ Effect} + \underbrace{\frac{e^{-\beta_0 dist}[2e^{-\beta_0 dist}-(n-2)\widetilde{\beta}]\alpha_{1i}}{(2e^{-\beta_0 dist}+\widetilde{\beta})[2e^{-\beta_0 dist}-(n-1)\widetilde{\beta}]}\phi_1}_{Direct\ Cost\ Effect}$$

$$+ \underbrace{\frac{\widetilde{\beta}e^{-\beta_0 dist}\left(\sum_{j\neq i}^{n-1}\alpha_{1j}\right)}{(2e^{-\beta_0 dist}+\widetilde{\beta})[2e^{-\beta_0 dist}-(n-1)\widetilde{\beta}]}\phi_1}_{Strategic\ Cost\ Effect} \qquad (1.21)$$

The above equation suggests that changes in crude oil price are translated into changes in airfare through two market channels: demand-side and supply-side. The following provides intuitive descriptions of the demand-side effect, as well as the two supply-side effects:

- **Demand effect**: The demand effect captures how crude oil price changes affect air travel demand. This effect is positive according to our previous discussion. An increase (decrease) in crude oil price pushes up (down) gasoline price, leading to higher (lower) air travel demand as driving becomes relatively more (less) costly. The higher (lower) demand for air travel causes airfare to rise (fall). This demand effect is stronger in shorter distance markets as driving is a closer substitute for flying at shorter distances.

- **Direct cost effect**: The direct cost effect captures the portion of airline i's optimal airfare response to changes in its own marginal cost, where the marginal cost changes are driven by changes in crude oil price. This direct cost effect is positive, and therefore consistent with the argument that an increase (decrease) in crude oil price causes an increase (decrease) in jet fuel price. The increase (decrease) in jet fuel price causes an increase (decrease) in the airline's own marginal cost, which then causes an increase (decrease) in the airline's optimal airfare.

- **Strategic cost effect**: The strategic cost effect captures the extent to which airline i's optimal airfare responds to changes in the marginal cost of rival airlines, where the rival airlines' marginal cost changes are driven by changes in crude oil price. This strategic cost effect results from the strategic interdependence across competing oligopolistic firms in a market, a feature of our model that results from the assumed Bertrand-Nash price-setting game played between airlines. The strategic cost effect is positive, reflecting the argument that an increase (decrease) in crude oil price increases (decreases) the marginal cost and

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consequently the airfare of an airline's rivals, which causes the airline to increase (decrease) its original airfare in response to the increase (decrease) in airfare of its rivals. Due to the strategic interdependence across competing oligopolistic airlines, it is important to note that the strategic effect facilitates a positive correlation between an airline's fare and crude oil price, even in an extreme situation in which the airline's own marginal cost is insensitive to crude oil price changes.

Proposition 1: *The marginal effect of crude oil price on an airline's optimal airfare is always positive, i.e., for $i = 1, 2, \ldots, n$: $\frac{\partial P_i^*}{\partial P_c} > 0$.*

The inequality in **Proposition 1** holds given $2\beta - (n-1)\tilde{\beta} > 0$ according to **Lemma 1** and the positive correlation among energy prices, i.e. $\delta_1, \phi_1 > 0$. **Proposition 1** implies that as crude oil price increases (decreases), the equilibrium airfare charged by airline i also increases (decreases). As suggested by Zimmerman and Carlson (2010), "a positive cost pass-through rate means that some portion of a marginal cost change will be passed through to price regardless of the level of competition".

1.3.3.2 The impact of an airline's jet fuel hedging decision on the cost pass-through rate

We now consider how the size of the pass-through from changes in crude oil price to airfare may be affected by an airlines' fuel hedging strategy. Airline service is heavily dependent on the price and availability of jet fuel. High volatility in fuel costs, increased fuel price, and significant disruptions in the supply of aircraft fuel can have a significant negative impact on airlines' regular operations. Airlines often enter into fuel hedging contracts, such as forward contracts, futures contracts, options, swaps, and collars, to lock in future fuel prices and thus reduce their exposure

to rising fuel costs.[19] We expect airlines that extensively use fuel hedging contracts are likely to experience a smaller impact from short-term fuel price swings resulting from crude oil market fluctuation. This effect is captured in our model by a relatively small α_{1i} for airline i in the marginal cost equation, which is equation (16) above. **Proposition 2** summarizes how the model captures the impact of airline jet fuel hedging decisions on the size of pass-through from changes in crude oil price to airfare:

Proposition 2: *The size of pass-through from changes in crude oil price to an airline's optimal fare is greater the larger parameter α_{1i} is in the airline's marginal cost function, i.e. for*

$$i, j = 1, 2, \ldots, n, i \neq j : \frac{\partial P_i^*}{\partial P_c} > \frac{\partial P_j^*}{\partial P_c}, \textbf{\textit{if }} \boldsymbol{\alpha_{1i}} > \boldsymbol{\alpha_{1j}}.$$

The proof of **Proposition 2** follows from the difference in the following partial derivatives:

$$\frac{\partial P_i^*}{\partial P_c} - \frac{\partial P_j^*}{\partial P_c} = \frac{\beta[2\beta - (n-1)\tilde{\beta}]\phi_1}{(2\beta + \tilde{\beta})[2\beta - (n-1)\tilde{\beta}]}\left(\alpha_{1i} - \alpha_{1j}\right) = \frac{\beta\phi_1}{(2\beta + \tilde{\beta})}\left(\alpha_{1i} - \alpha_{1j}\right) \tag{1.22}$$

Given that $\beta, \tilde{\beta} > 0$ and $\phi_1 > 0$, $\frac{\partial P_i^*}{\partial P_c} - \frac{\partial P_j^*}{\partial P_c} > 0$ holds if and only if $\alpha_{1i} - \alpha_{1j} > 0$.

Alternatively, by **Lemma 1**, we can describe **Proposition 2** using the following equation:

$$\frac{\partial\left\{\frac{\partial P_i^*}{\partial P_c}\right\}}{\partial \alpha_{1i}} = \frac{\beta[2\beta - (n-2)\tilde{\beta}]\phi_1}{(2\beta + \tilde{\beta})[2\beta - (n-1)\tilde{\beta}]} > 0; \text{ when } 2\beta - (n-1)\tilde{\beta} > 0 \tag{1.23}$$

The above equation states that the larger α_{1i} is, the larger the impact of crude oil price on airline i's optimal price level. Intuitively, we may rationalize this effect in the following way: airlines who enter jet fuel hedging contracts, which cause a smaller α_{1i}, tend to experience smaller changes in their marginal cost from crude oil price shocks compared to airlines that do not use fuel

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[19] There are considerable studies that focus on how airline fuel hedging strategies affect airlines in terms of firm market value and risk management (see Carter, Rogers and Simkins (2006a, 2006b), Morrell and Swan (2006), and Treanor et al. (2014)).

hedging contracts. In this case, the latter airlines are more likely to pass along the crude oil price shocks to consumers through airfare.

1.3.3.3 The impact of market competition on the cost pass-through rate

We now consider how the size of pass-through from changes in crude oil price to airfare may vary with the level of market competition, where the degree of market competition is measured in the model by the number of airlines that compete in the market, n. The impact of air travel market competition intensity on the size of crude oil price pass-through to airfare is described in the following proposition:

Proposition 3: *The extent of pass-through from changes in crude oil price to airfare increases with the number of firms in the market, that is, the pass-through rate is greater in more competitive markets than in less competitive markets, i.e. for $i = 1,2, \ldots, n$: $\dfrac{\partial\left\{\frac{\partial P_i^*}{\partial P_c}\right\}}{\partial n} > 0$.*

The proof of **Proposition 3** follows from the following partial derivative:

$$\frac{\partial\left\{\frac{\partial P_i^*}{\partial P_c}\right\}}{\partial n} = \frac{\gamma\widetilde{\beta}\delta_1}{\left[2\beta-(n-1)\widetilde{\beta}\right]^2} + \frac{\beta\widetilde{\beta}^2\phi_1\left(\sum_{j=1}^{n}\alpha_{1j}\right)}{(2\beta+\widetilde{\beta})\left[2\beta-(n-1)\widetilde{\beta}\right]^2}$$

$$= \frac{e^{-\gamma_0 dist}\widetilde{\beta}\delta_1}{\left[2e^{-\beta_0 dist}-(n-1)\widetilde{\beta}\right]^2} + \frac{e^{-\beta_0 dist}\widetilde{\beta}^2\phi_1\left(\sum_{j=1}^{n}\alpha_{1j}\right)}{(2e^{-\beta_0 dist}+\widetilde{\beta})\left[2e^{-\beta_0 dist}-(n-1)\widetilde{\beta}\right]^2} \qquad (1.24)$$

The sign of the above equation is positive given $\beta, \widetilde{\beta} > 0$ and $\gamma, \alpha_{1j}, \delta_1, \phi_1 > 0$, suggesting that an increase in n corresponds to a higher pass-through rate. As the market becomes more competitive with a growing number of firms, these firms are likely to compete more aggressively in prices, leaving smaller and smaller profit margins. A profit maximizing firm will quickly adjust its optimal price after a cost shock, holding the belief that its rivals will react similarly to the cost shock. As such, a cost shock is likely to pass-through into new equilibrium prices on a larger scale

when markets are more competitive. This interpretation complies with the argument made by Koopmans and Lieshout (2016) and Malina et al. (2012) that when markets become more competitive, profits margins decline, which leaves little room for airlines to absorb costs without passing through cost increase to prices. In summary, airlines are more likely to pass cost changes to airfare when market competition is more intense.

1.3.3.4 The impact of market distance on the cost pass-through rate

Our theory suggests that consumer preference between air travel and private automobile travel depends on the relevant ground transport cost in transporting them from origin to destination. An essential factor that determines the ground transport cost is the market distance between the two endpoints of the market. We use the air travel non-stop flying miles between the origin and destination as an index for the driving distance between the two endpoints. As revealed in our specification of air travel demand in equations (2), (3), (4) and (5), market distance affects both the level of air travel demand (captured by $\gamma = e^{-\gamma_0 dist}$) and the elasticity of the air travel demand (captured by $\beta = e^{-\beta_0 dist}$). As revealed in equation (18), market distance influences Nash equilibrium prices both from influencing the level of demand through $e^{-\gamma_0 dist}$, and the elasticity of demand through $e^{-\beta_0 dist}$. Hence, we consider the overall impact of market distance on cost pass-through rate to be split into two effects: "*level effect*" and "*elasticity effect*". For a given number of firms in the market, the overall effect is calculated by partially differentiating the cost pass-through rate equation (equation (21)) with respect to market distance, which yields the following:

$$\frac{\partial\left\{\frac{\partial P_i^*}{\partial P_c}\right\}}{\partial dist} = \underbrace{\left(\frac{\delta_1}{2\beta-(n-1)\tilde{\beta}}\right)\frac{\partial\{e^{-\gamma_0 dist}\}}{\partial dist}}_{Level\ Effect} +$$

$$\left(\frac{\partial\left\{\frac{1}{2e^{-\beta_0 dist}-(n-1)\tilde{\beta}}\right\}}{\partial dist}\right)(\delta_1\gamma) + \left(\frac{\partial\left\{\frac{e^{-\beta_0 dist}\left[2e^{-\beta_0 dist}-(n-2)\tilde{\beta}\right]}{\left(2e^{-\beta_0 dist}+\tilde{\beta}\right)\left[2e^{-\beta_0 dist}-(n-1)\tilde{\beta}\right]}\right\}}{\partial dist}\right)(\phi_1\alpha_{1i})$$

$$+ \underbrace{\left(\frac{\partial\left\{\frac{\tilde{\beta}e^{-\beta_0 dist}}{\left(2e^{-\beta_0 dist}+\tilde{\beta}\right)\left[2e^{-\beta_0 dist}-(n-1)\tilde{\beta}\right]}\right\}}{\partial dist}\right)\left(\phi_1\sum_{j\neq i}^{n-1}\alpha_{1j}\right)}_{Elasticity\ Effect}$$

$$= \underbrace{-\frac{\gamma_0\delta_1\gamma}{2\beta-(n-1)\tilde{\beta}}}_{Level\ Effect\ (-)} + \underbrace{\frac{2\beta_0\delta_1\gamma\beta}{\left[2\beta-(n-1)\tilde{\beta}\right]^2} + \frac{(n-1)\beta_0\tilde{\beta}^2\left[4\beta-(n-2)\tilde{\beta}\right]\beta\phi_1\alpha_{1i}}{\left(2\beta+\tilde{\beta}\right)^2\left[2\beta-(n-1)\tilde{\beta}\right]^2} + \frac{\beta_0\tilde{\beta}\left[4\beta^2+(n-1)\tilde{\beta}^2\right]\beta\phi_1\sum_{j\neq i}^{n-1}\alpha_{1j}}{\left(2\beta+\tilde{\beta}\right)^2\left[2\beta-(n-1)\tilde{\beta}\right]^2}}_{Elasticity\ Effect\ (+)}$$

Therefore,

$$\frac{\partial\left\{\frac{\partial P_i^*}{\partial P_c}\right\}}{\partial dist} = \underbrace{-\frac{\gamma_0\delta_1 e^{-\gamma_0 dist}}{2e^{-\beta_0 dist}-(n-1)\tilde{\beta}}}_{Level\ Effect\ (-)} +$$

$$\underbrace{\frac{2\beta_0\delta_1 e^{-\gamma_0 dist}e^{-\beta_0 dist}}{\left[2e^{-\beta_0 dist}-(n-1)\tilde{\beta}\right]^2} + \frac{(n-1)\beta_0\tilde{\beta}^2\left[4e^{-\beta_0 dist}-(n-2)\tilde{\beta}\right]e^{-\beta_0 dist}\phi_1\alpha_{1i}}{\left(2e^{-\beta_0 dist}+\tilde{\beta}\right)^2\left[2e^{-\beta_0 dist}-(n-1)\tilde{\beta}\right]^2}}_{} \tag{1.25}$$

$$\underbrace{+ \frac{\beta_0\tilde{\beta}\left[4e^{-2\beta_0 dist}+(n-1)\tilde{\beta}^2\right]e^{-\beta_0 dist}\phi_1\sum_{j\neq i}^{n-1}\alpha_{1j}}{\left(2e^{-\beta_0 dist}+\tilde{\beta}\right)^2\left[2e^{-\beta_0 dist}-(n-1)\tilde{\beta}\right]^2}}_{Elasticity\ Effect\ (+)}$$

The first term on the right-hand-side of equation (25), which we label the "*level effect*", is influenced by $e^{-\gamma_0 dist}$, but not influenced by $e^{-\beta_0 dist}$. The "*level effect*" measures the extent to which market distance affects airlines' adjustment of their optimal prices as a response to crude oil price changes driven by the likelihood of consumers switching between air travel and private automobile travel due to changes of ground transport cost induced by gasoline price changes. Intuitively, an increase in crude oil price leads to an increase in gasoline price, which increases the expense of driving relative to the expense of air travel. Air travel in this case becomes more attractive, shifting the demand curve outward as consumers switch from driving to air travel. The

magnitude of the shift of air travel demand depends on the market distance between origin and destination. The magnitude of the demand shift is large for short distance travel compared with long distance travel because it is much easier for consumers to switch between driving and flying when the origin and destination are close to each other. Thus, we expect there are more consumers switching from driving to flying for short distance travel when gasoline price increases, i.e. gasoline price changes are predicted to be more impactful on consumers decision to drive versus fly in shorter distance markets.

The *level effect* term in equation (25) is negative, implying that a shorter market distance causes a higher cost pass-through rate owing to the *level effect*. We use Figure 1.5 to better illustrate the *level effect*. In order to focus on the impact of the *level effect*, we keep the elasticity of air travel demand constant across markets of different distances. A simplified assumption to illustrate the *level effect* is to let the initial demand curve, D_0, represent both the initial short-distance and long-distance market demand. In addition, the associated equilibrium price level, P_0, which is found by equating the initial marginal cost curve, MC_0 to the initial marginal revenue curve, MR_0 at E_0 for a typical oligopolistic firm i, represents both the initial short-distance and long-distance equilibrium market price level.

Consider now a cost shock resulting from an increase in crude oil price level, which shifts MC_0 upward to MC_1. It is expected that this shock is more impactful in the short-distance market by shifting the initial short-distance market demand, D_0, rightward to D_1^S, which is a larger shift than the resulting new long-distance market demand, D_1^L. The associated new marginal revenue curves for the new short-distance and new long-distance market demand are MR_1^S, MR_1^L respectively. The new profit-maximizing price levels, P_1^S, P_1^L, corresponding to the new short- and long-distance market demand are found by equating the new marginal revenue, MR_1^S, MR_1^L, to the

new marginal cost curves, MC_1, at E_1^S, E_1^L respectively. It is evident that a larger rightward shift of short-distance market demand results in a greater equilibrium increase in airfare, i.e. $\Delta P_i^S = P_1^S - P_0 > \Delta P_i^L = P_1^L - P_0$, suggesting a higher pass-through rate for a given cost shock, ΔMC, in a shorter distance market than it is in a longer distance market. Meanwhile, the nature of the oligopolistic market structure suggests that this cost-price pass-through is likely to be incomplete for a typical oligopolistic firm i. That is, the maximum change in equilibrium airfare tends to be less than the change in marginal cost for a given cost shock, i.e. $\Delta P_i^S \le \Delta MC$.

Figure 1.5 Illustrating the *level effect* using a simple diagram
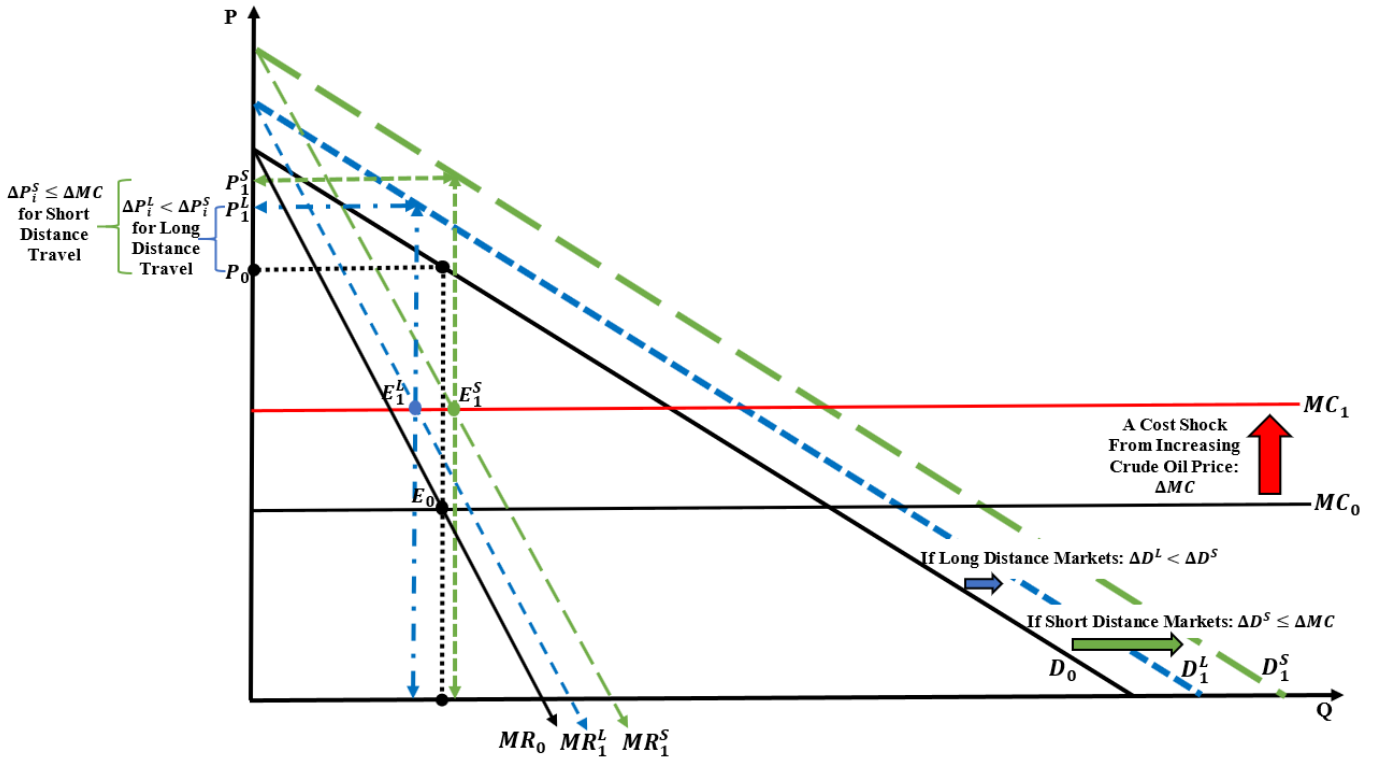
The last three terms in equation (25) together capture what we call the *elasticity effect* of market distance on the cost pass-through rate. The *elasticity effect* measures the extent to which market distance affects an airline's optimal airfare response to crude oil price changes based on consumers' sensitivities to changes of airfare. The intuition is that short-distance travelers tend to

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be more sensitive to airfare changes than long-distance travelers, simply because driving is often not a realistic alternative to air travel in long distance markets. As such, we would expect airlines to pass along a crude oil price induced cost shock to airfare more heavily to long distance air travelers given their less elastic air travel demand compared to consumers in short-haul distance markets. Another way to understand airlines' pass-through behavior in this analysis is to think about how much output they have to sacrifice to pass on a certain amount of the change in their marginal costs.[20] A pass-through will be larger for the less elastic long-distance air travel demand because the reduction of quantity demand is smaller for a given increase in airfare, thus making passing the cost shock through to airfare more attractive than in short-haul distance markets.

In contrast to the negative impact of the *level effect* of market distance on cost pass-through rate in equation (25), the *elasticity effect* is positive, suggesting that the cost pass-through rate is smaller in shorter distance markets. We use Figure 1.6 to better illustrate the *elasticity effect*. When we consider the *elasticity effect*, we focus on analyzing differing elasticity of air travel demand between short-haul and long-haul markets, assuming no *level effect* is induced by differing market distance.

To simplify the illustration, we assume the initial equilibrium airfare for the more elastic short-distance market is the same level as the initial equilibrium airfare for the less elastic long-distance market, P_0, which is found by equating their associated marginal revenue curves, MR_S, MR_L, to the initial marginal cost curve, MC_0, at E_0^S, E_0^L, respectively. Consider now a cost shock resulting from an increase in crude oil price level, causing and upward shift in marginal cost from MC_0 to MC_1. The new MC_1 curve intersects the short-distance marginal revenue curve, MR_S,

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[20] Cost pass-though: theory, measurement, and potential policy implications. RBB Economics, February 2014.

at E_1^S and the long-distance marginal revenue curve, MR_L, at E_1^L. The resulting new profit-maximizing price level for the long-distance market is notably greater than that for the short-distance market, i.e. $P_1^L > P_1^S$, suggesting a greater equilibrium increase in airfare for the less elastic long-distance market demand than in the more elastic short-distance market for a given cost shock, i.e. $\Delta P_i^L = P_1^L - P_0 > \Delta P_i^S = P_1^S - P_0$. In other words, the changes in Figure 1.6 reveal that the *elasticity effect* drives a higher pass-through rate for a given cost shock, ΔMC, in a short distance market compared to a long distance market. Similar to the previous discussion, it is expected that the maximum change in equilibrium airfare is less than the change in marginal cost for a given cost shock of ΔMC, i.e. $\Delta P_i^L \leq \Delta MC$.

Figure 1.6 Illustrating the *elasticity effect* using a simple diagram
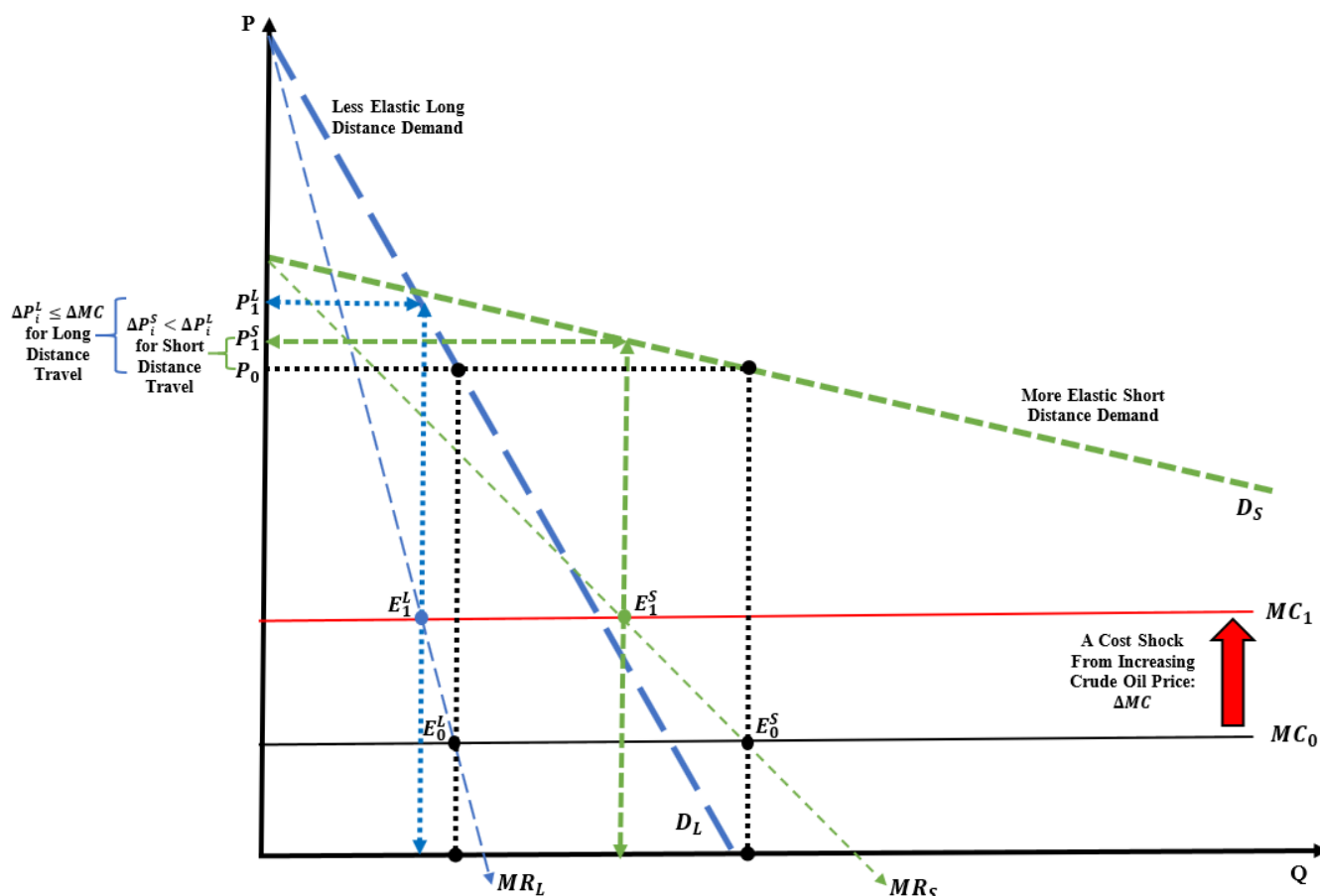
In summary, it is important to note that the overall effect of market distance between origin and destination on the size of pass-through from changes in crude oil price to airfare is determined by the relative strengths of two offsetting effects, the *level effect* and *elasticity effect*. This result is summarized in **Proposition 4**.

Proposition 4: *The impact of market distance between origin and destination on the size of pass-through from changes in crude oil price to airline market fare levels is governed by two offsetting effects: a negative "level effect" and a positive "elasticity effect". Specifically, the negative "level effect" implies that the cost pass-through rate is smaller in longer distance markets, while the positive "elasticity effect" implies that the cost pass-through rate is larger in longer distance markets. Therefore, the sign of the overall pass-through rate effect of market distance is determined by the relative strengths of the "level effect" and the "elasticity effect".*

1.4 Empirical Analysis

We now analyze whether the theoretical predictions above are supported by systematic patterns across a sample of U.S. domestic origin-destination air travel markets. We start by describing the data sample used in the empirical analysis and then describe the empirical model used for analyzing the data, followed by a discussion of results from the empirical model.

1.4.1 Data

We use data from three main sources. The airline ticket information data are the Passenger Origin-Destination Survey of the U.S. Department of Transportation (database DB1B). These data are a 10% quarterly random sample of all airline tickets. The DB1B database provides information on flight fares; itinerary (origins, destinations, and all connecting airports on a given itinerary); the

identity of ticketing and operating carriers for each flight segment on the itinerary; the type of ticket (i.e. round-trip or one-way); the number of passengers traveling on the itinerary at a given fare in each origin-destination pair; itinerary miles flown in transporting the passenger from origin to destination; and non-stop flight distance between the origin and destination.[21] Following Aguirregabiria and Ho (2012), information on the population of each origin and destination city is based on the Population Estimates Program (PEP) of the U.S. Census Bureau, which produces annual population estimates under the category "Cities and Towns (Incorporated Places and Minor Civil Division)."[22] We use the energy price data from the U.S. Energy Information Administration (EIA) under "short-term energy outlook,"[23] including gasoline, jet fuel, and crude oil prices[24]. Last, we collected the information regarding airlines' jet fuel hedging strategy adopted in our data file from their Securities and Exchange Commission (SEC) filings (i.e. their 10-K filing).

1.4.1.1 Sample Selection

The DB1B raw data file contains millions of tickets for each quarter during the year. For instance, the number of records in the third quarter of 2013 is 5,749,897. To construct our working sample, we focus on the last two quarters of 2013,[25] and all four quarters of 2014 and 2015, a total

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[21] The URL of this data source is: http://www.transtats.bts.gov/Tables.asp?DB_ID=125.

[22] The URL of this data source is: http://www.census.gov/popest/data/index.html.

[23] The URL of the data source is: https://www.eia.gov/forecasts/steo/query/.

[24] Crude oil is represented by *Brent Crude Oil* since this is the primary energy index that most US airlines follow for fuel hedging; gasoline is using "all grades retail price including taxes US average;" and jet fuel price is the price of "jet fuel refiner price to end users." All energy prices are deflated in the 2014 dollar using consumer price index (CPI) that was obtained from the Bureau of Labor Statistics (BLS).

[25] Before this sample period, American Airlines and US airways announced plans to merge in February 2013 and was approved by US Airways shareholders in July 2013. This merger was challenged by the Department of Justice August 2013 but soon was settled in November 2013. We assume that the market price change that might be influenced by

of ten quarters of data. As previously shown in Figure 1.1, this time period spans relatively substantial fluctuations in crude oil price, and these fluctuations are important for empirical identification of the relationships between changes in crude oil price and airfares, which is key to achieve the key objectives of the analysis.

We construct our DB1B working sample in the following manner:

- Following Brueckner and Spiller (1994) and Berry, Carnall, and Spiller (2006), we keep only round-trip itineraries within the continental U.S. with at most four segments (i.e. no more than three intermediate stops). We eliminate all itineraries with market fares less than $50 or greater than $2,000.

- A *market* is defined as a directional pair of an origin and a destination airport. For example, a direct flight from Atlanta to Boston is a different market than from Boston to Atlanta. This definition allows for the characteristics of the origin city to affect consumers' air travel demand. As in Berry, Carnall, and Spiller (2006), the geometric mean of the population estimates in 2014 of the end-point cities characterizes a measure of the market size.

- A *product* is defined as a unique combination of itinerary and operating carrier. A non-stop flight from Atlanta to Boston operated by American Airline, for instance. We focus on products that use a single operating carrier for all segments of a given itinerary, i.e.

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the AA-US Airways merger was realized when it was announced in the beginning of 2013 and thus our analysis of airline market fare during our sample period avoids the examination of the market price change that may contribute to the increasing market power caused by this merger. The idea is similar to the statement that Kim and Singal (1993) made in their study that "exercise of market power does not have to wait until merger completion…even without an explicit price-fixing agreement, the mere anticipation of a merger would make the participating firms more cooperative."

pure online products. Table 1.2 lists the names and associated airline code of the 21 carriers in our sample.

- Product *price* and product *quantity* sold are obtained by averaging the market fare and aggregating the number of passengers, respectively, according to our definition of product. Thus, in the collapsed data, a product is a unique observation during a given time period.

Table 1.2 List of Airlines in the Sample

Airline Code	Airline Name	Airline Code	Airline Name
AA	American Airlines	OO	SkyWest Airlines
AS	Alaska Airlines	RP	Chautauqua Airlines
B6	JetBlue Airways	S5	Shuttle America
DL	Delta Airlines	SY	Sun Country Airlines
EV	ExpressJet Airlines	UA	United Airlines
F9	Frontier Airlines	US	US Airways
FL	AirTran Airways	VX	Virgin America
G4	Allegiant Airlines	WN	Southwest Airlines
G7	GoJet Airlines	YV	Mesa Airlines
HA	Hawaiian Airlines	YX	Midwest Airlines
NK	Spirit Airlines		

Unfortunately, one limitation of the DB1B data is that it does not contain passenger-specific information and some important elements of product differentiation, such as departure times, how far in advance the ticket is purchased and length-of-stay requirements. The energy price data from EIA is available as a daily market spot price. With only quarterly airline data, we restrict our selection of energy prices to also be quarterly, i.e. the Brent crude oil, jet fuel, and gasoline prices are quarterly averaged market spot prices obtained from the EIA database.

1.4.1.2 Data Summary

Table 1.3 reports the summary statistics of our sample. Overall, we have 615,242 observations/products in our sample and 147,073 markets based on our definitions of *products* and *markets* respectively. The quarterly average airfare, crude oil price, jet fuel price, and gasoline price in the sample are approximately $266, $81.53/barrel (or $1.94/gallon), $2.33/gallon, and $3.07/gallon respectively. The average market distance across all products is approximately 1414 miles. To control for the likelihood that larger markets will have greater demand for air travel, we include the variable of *population* measured by the geometric mean of the population size in the origin and destination cities. Airfare is affected by market structure, product differentiation and other market or product level characteristics. To control for these market and product-level characteristics, we include other variables in the analysis.

N_airline_mkt is a variable we constructed to serve as a measure of actual market competition, calculated by summing the number of distinct carriers serving the relevant market. A monopoly market is one with only one airline serving the market. There are at maximum 11 airlines competing in a market, and on average 4 airlines offering flight services in a market.

To control for the likelihood that the threat of entry may affect equilibrium market fare, we include variables *Threat_all* and *Threat_non_legacy*, as measures of potential market competition. Following Gayle and Wu (2013) and Goolsbee and Syverson (2008), *Threat_all* is obtained by computing the number of all the distinct carriers that are present at both endpoints of a market without actually serving the market; and *Threat_non_legacy* is obtained by computing the number of all the distinct non-legacy carriers that are present at both endpoints of a market without actually serving the market. Following Berry and Jia (2010) and Brueckner, Lee and Singer (2013), carriers that are normally considered as legacy carriers include American Airlines, United, Delta, US

Airways, Alaska, Midwest, and Hawaiian Airlines.[26] Non-legacy carriers include all the carriers in the dataset that are any of the seven carriers listed above as legacy carriers. The maximum number of carriers that place an entry threat without serving the market is 10, whereas the maximum number of non-legacy carriers that place an entry threat without serving the market is 7. The three variables described above, *N_airline_mkt*, *Threat_all*, and *Threat_non_legacy* capture the structure and intensity of competition in each market, and used to control for the impact of these market structure factors on equilibrium airfares as well as their impact on the size of cost pass-through.

Carriers may offer both non-stop and connecting service in a market. Consumers likely value the two types of products differently. To capture the difference in demand for these two types of air travel products, we use the variable *Interstop* as one measure of travel convenience of an itinerary. The variable is constructed by summing the number of intermediate stops in a product's itinerary. Therefore, it is expected that the more intermediate stops associated with an itinerary, the less convenient the air travel product is considered to be. However, there may exist products that have the same number of intermediate stops in an origin and destination market; but because the location(s) of the intermediate stop airport(s) are different, their associated itinerary flying miles will differ and thus exhibit different relative routing qualities. Following Chen and Gayle (2018), Gayle and Wu (2015), and Gayle and Le (2015), we use *Inconvenience* to measure the product routing quality which is not captured by the *Interstop* variable. This variable is computed by dividing the itinerary miles flown from origin to destination by its corresponding

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[26] To construct all the entry threat variables, we place less restrictions on the DB1B dataset by not solely focusing on roundtrip itineraries. The less restrictive data thus includes carriers that may only place entry threat to the incumbents in a market by providing one-way flights at both endpoints without actually serving the market. These airlines will not be included in our final dataset, but are only used to measure the potential market competition.

non-stop radian distance. Thus, if an itinerary is a non-stop flight, then its *Inconvenience* measure is 1. The maximum *Inconvenience* measure of a product in the data is about 3.7. This means travelers cover a 3.7 times longer distance with this product than the direct flight distance.

Origin_Presence is a variable that measures the size of airlines' operations at the market origin airport. This variable also captures the extent to which airlines use an origin airport as their hub. *Origin_Presence* is constructed by aggregating the number of destinations that an airline connects with the origin city using non-stop flights. An airport from which an airline serves many destinations using non-stop flights is more likely to be a hub or a focus city for the airline, possibly providing better services, such as more frequent and convenient departure times for passengers. The summary statistics show that airlines serve, on average, about 26 different cities from the relevant market's origin cities.

Fuel cost is one major component of airlines operating expenses. To protect against sudden losses from rising fuel prices or sudden gains from decreasing fuel prices, airlines usually use some form of hedging contract instrument to lock in fuel prices over a period of time, thus helping to mitigate fluctuations in the overall operating cost of the airline. We construct a zero-one dummy variable *Hedge*, which is assigned a value of 1 one if the carrier uses jet fuel hedging contracts. On average, about 81% of products provided are provided by carriers that use hedging contracts.

Table 1.3 Summary Statistics

Variables	Mean	Std. Dev.	Min	Max
Airfare* (dollars)	266.4667	107.9482	49.7374	1974.787
Crude Oil Price* (dollars/barrel)	81.53147	27.08791	43.32127	112.0041
Jet Fuel Price* (cents/gallon)	233.575	64.54691	136.8773	302.8977
Gasoline Price* (cents/gallon)	307.1999	53.20798	225.2109	374.6044
Quantity (numbers of passengers per product)	81.00224	375.4612	1	10294
Interstop	1.006485	.5025355	0	3
Inconvenience	1.242713	.3084797	.9972678	3.731755
Origin_Presence	26.49011	24.91389	0	126
N_airline_mkt	3.736166	2.166795	1	11
Threat_all	1.139986	1.141304	0	10
Threat_non_legacy	0.5373089	0.7417947	0	7
Non-stop flight distance (miles)	1414.693	634.7927	70	2783
Population	627422.8	606798.2	3017.846	5783171
Hedge	.8151882	.3881452	0	1
Number of Products	615242			
Number of Markets	147073			

* Inflation-adjusted in 2014 dollar.

In the next section, we use a simple reduced-form regression to empirically test the impact of crude oil price changes on airfare, and factors that affect the size of the pass-through.

1.4.2 Empirical Model

Based on our theory, it has been argued that there exists a positive pass-through relationship from changes in crude oil price to airline market fare, and the size of this pass-through is affected by some market characteristics. In accordance with our theoretical predictions, we empirically estimate and test how various measures of market and airline characteristics affect the size of pass-through: airline jet fuel hedging decisions, market competition and market distance between origin and destination.

1.4.2.1 Reduced-form Regression Models

Our empirical analysis relies on the following two reduced-form model specifications:

Model I:

$$log(P_{imt}) = \theta_0 + \theta_1 \, log(P_{c,imt}) + \theta_2 N\_airline\_mkt_{imt}$$

$$+\theta_3 \, log(P_{c,imt}) \times N\_airline\_mkt_{imt} + \theta_4 Threat\_all_{imt}$$

$$+\theta_5 \, log(P_{c,imt}) \times Threat\_all_{imt} + \theta_6 \, log(distance_{imt})$$

$$+\theta_7 \, log(P_{c,imt}) \times log(distance_{imt}) + \theta_8 Hedge_{imt}$$

$$+\theta_9 \, log(P_{c,imt}) \times Hedge_{imt} + \theta_{10} Interstop_{imt}$$

$$+\theta_{11} Inconvenience_{imt} + \theta_{12} Origin\_Presence_{imt}$$

$$+\theta_{13} \, log(Population_{imt}) + \eta_t + Origin_m + Dest_m + \varepsilon_{imt} \qquad (1.26)$$

Model II:

$$log(P_{imt}) = \theta_0 + \theta_1 \, log(P_{c,imt}) + \theta_2 N\_airline\_mkt_{imt}$$

$$+\theta_3 \, log(P_{c,imt}) \times N\_airline\_mkt_{imt} + \theta_4 Threat\_non\_legacy_{imt}$$

$$+\theta_5 \, log(P_{c,imt}) \times Threat\_non\_legacy_{imt} + \theta_6 \, log(distance_{imt})$$

$$+\theta_7 \, log(P_{c,imt}) \times log(distance_{imt}) + \theta_8 Hedge_{imt}$$

$$+\theta_9 \, log(P_{c,imt}) \times Hedge_{imt} + \theta_{10} Interstop_{imt}$$

$$+\theta_{11} Inconvenience_{imt} + \theta_{12} Origin\_Presence_{imt}$$

$$+\theta_{13} \, log(Population_{imt}) + \eta_t + Origin_m + Dest_m + \varepsilon_{imt} \qquad (1.27)$$

The dependent variable in each model is the airfare of product i in market m at time t, represented by P_{imt}. Both model specifications include the following control variables: P_c;

N_airline_mkt; *distance*; *Hedge*; *Interstop*; *Inconvenience*; *Origin_Presence*; *Population*; time

fixed effects (η_t); origin fixed effects; and destination fixed effects. P_c represents crude oil price.

Model I and II differ from each other by how potential entry threat is measured. Specifically, in

Model I we use the number of all distinct airlines that are present at both endpoints without serving

the market, i.e. *Threat_all*; while in Model II we use the number of all non-legacy carriers that are

present at both endpoints without serving the market, i.e. *Threat_non_legacy*.

In accordance with our theoretical prediction in the model section, we rely on reduced-

form regression analysis to identify the pass-through rate of changes in crude oil price to airfare,

and examine how market competition, distance and airline-specific decisions on hedging influence

the size of the pass-through. Based on the linear regression model specifications above, the pass-

through rate (PTR) of changes in crude oil price to airfare is defined by:

$$PTR = \frac{\partial \log(P)}{\partial \log(P_c)} = \theta_1 + \theta_3 N\_airline\_mkt_{imt} + \theta_5 Threat\_all$$

$$+\theta_7 \log(distance) + \theta_9 Hedge \qquad (1.28)$$

$$PTR = \frac{\partial \log(P)}{\partial \log(P_c)} = \theta_1 + \theta_3 N\_airline\_mkt_{imt} + \theta_5 Threat\_non\_legacy$$

$$+\theta_7 \log(distance) + \theta_9 Hedge \qquad (1.29)$$

Equation (28) and equation (29) reveal that the size of the pass-through rate is influenced

by variables, *N_airline_mkt*, *Threat_all*, *Threat_non_legacy*, *log(distance)*, and *Hedge*. As such,

the primary parameters of interest are: θ_1, θ_3, θ_5, θ_7 and θ_9.

1.4.2.2 Regression Results

The reduced-form regression results are reported in Table 1.4. Given the fact that airlines

jet fuel hedging decisions are airline-specific characteristics that are included in the regressions,

then airline fixed effects cannot be included in the regressions.

We use the logarithm of airfare and crude oil price, thus the coefficient estimate on $log(P_c)$ measures the elasticity of airfare with respect to crude oil price, i.e. the percentage change in airfare associated with a given percentage change in crude oil price. The coefficient estimates of $log(P_c)$ in both models have the expected positive signs and are statistically significant. Without considering the impact of other market characteristics, the coefficient estimates on $log(P_c)$ reveal that, on average, a 10% increase in crude oil price yields about a 0.61% to 0.77% increase in airfare. This result provides direct evidence that a given percentage change in crude oil price translates into a certain percentage change in airfare. In particular, we find evidence of a direct positive impact of crude oil price shocks on airfares. Our estimate of the pass-through rate is similar to the pass-through estimate in Duplantis (2010), 0.08, with constant capacity.

The coefficient estimates of $N\_airline\_mkt$ are both statistically significant. This parameter is introduced to capture the role of actual market competition in influencing the market airfare. Both estimates have expected negative signs, suggesting that the more airlines actually serving the market (implying higher competition in the market), the lower the airfare. For example, the estimated coefficient on $N\_airline\_mkt$ indicates that, on average, each additional carrier active in an origin-destination market lowers airfare of a typical product in the market by 3.5% to 3.7%.

The coefficient estimates on $Threat\_all$ and $Threat\_non\_legacy$ measure the role of potential market competition in influencing the market airfare. The two variables are expected to have a negative impact on the airfare rationalized by the fact that a greater number of entry threats from potential entrants places downward pressure on the market airfare. The coefficient estimate on $Threat\_non\_legacy$ has the expected negative sign and is statistically significant, suggesting that each additional non-legacy carrier that threatens to enter an origin-destination market lowers

the market fare by 2.39% on average. The coefficient estimate for $Threat\_all$ does not have the expected sign and is not statistically significant at the conventional levels of statistical significance.

In order to assess the role of market competition level in influencing the size of pass-through from changes in crude oil price to airfare,[27] we focus on the interaction terms: $log(P_c) \times N\_airline\_mkt, log(P_c) \times Threat\_all$ in Model I and $log(P_c) \times N\_airline\_mkt, log(P_c) \times Threat\_non\_legacy$ in Model II. The interaction terms of $log(P_c) \times N\_airline\_mkt$ in both models are statistically significant at conventional levels of statistical significance. In Model I, the coefficient estimate on $log(P_c) \times N\_airline\_mkt$ suggests that the more airlines competing in an origin-destination market, the greater the size of pass-through in that market. Specifically, it implies that, on average, each additional air carrier actually serving an origin-destination market increases the pass-through elasticity by approximately 0.006 percentage points. The coefficient estimate on $log(P_c) \times Threat\_all$ in Model I is not statistically significant, so we focus on the interpretation of the coefficient estimate of $log(P_c) \times Threat\_non\_legacy$ in Model II, i.e. $\widehat{\theta_5} = 0.00757$. This estimate implies that each additional non-legacy carrier placing an entry threat to an origin-destination market raises the pass-through elasticity in the market by around 0.008 percentage points. In summary, the empirical results validate our theoretical prediction in **Proposition 3** that greater market competition on average increases the size of pass-through from changes in crude oil price to airfare.

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[27] This impact of market structure in the pass-through rate is captured by the parameters θ_3, θ_5, i.e. $\theta_3 = \frac{\partial PTR}{\partial N\_airline\_mkt}$ in Model I and II, $\theta_5 = \frac{\partial PTR}{\partial Threat\_all}$ in Model I and $\theta_5 = \frac{\partial PTR}{\partial Threat\_non\_legacy}$ in Model II.

Table 1.4 Reduced-form Airfare Regression Models Estimated by Ordinary Least Squares

	Model I	Model II
	Dependent Variable: $log(P)$	Dependent Variable: $log(P)$
$log(P_c)$ (θ_1)	0.0766***	0.0611***
	(0.0187)	(0.0180)
$N\_airline\_mkt$ (θ_2)	-0.0369***	-0.0350***
	(0.00263)	(0.00266)
$log(P_c) \times N\_airline\_mkt$ (θ_3)	0.00604***	0.00554***
	(0.000587)	(0.000596)
$Threat\_all$ (θ_4)	0.00128	
	(0.00439)	
$log(P_c) \times Threat\_all$ (θ_5)	0.000627	
	(0.00100)	
$Threat\_non\_legacy$ (θ_4)		-0.0239***
		(0.00636)
$log(P_c) \times Threat\_non\_legacy$ (θ_5)		0.00757***
		(0.00146)
$log(distance)$ (θ_6)	0.394***	0.387***
	(0.0104)	(0.0101)
$log(P_c) \times log(distance)$ (θ_7)	-0.0162***	-0.0148***
	(0.00239)	(0.00232)
$Hedge$ (θ_8)	0.427***	0.425***
	(0.0122)	(0.0122)
$log(P_c) \times Hedge$ (θ_9)	-0.0840***	-0.0837***
	(0.00282)	(0.00282)
$Interstop$ (θ_{10})	0.0843***	0.0842***
	(0.000859)	(0.000859)
$Inconvenience$ (θ_{11})	0.240***	0.240***
	(0.00147)	(0.00147)
$Origin\_Presence$ (θ_{12})	0.00113***	0.00113***
	(0.0000213)	(0.0000213)
$log(Population)$ (θ_{13})	522.0*	522.6*
	(276.4)	(276.3)
$constant$ (θ_0)	-6373.9*	-6381.0*
	(3375.8)	(3375.4)
R^2	0.315	0.315
N	615242	615242
$\overline{PTR}$	0.04884[a]	0.03924[b]
	-0.03546[c]	-0.04446[d]

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Year and quarter dummies, origin and destination dummies are included in both Model I and II.

[a] $\overline{PTR} = \widehat{\theta_1} + \widehat{\theta_3} \times \overline{N\_airline\_mkt} + \widehat{\theta_5} \times \overline{Threat\_all} + \widehat{\theta_7} \times \overline{log(distance)}$

[b] $\overline{PTR} = \widehat{\theta_1} + \widehat{\theta_3} \times \overline{N\_airline\_mkt} + \widehat{\theta_5} \times \overline{Threat\_non\_legacy} + \widehat{\theta_7} \times \overline{log(distance)}$

[c] $\overline{PTR} = \widehat{\theta_1} + \widehat{\theta_3} \times \overline{N\_airline\_mkt} + \widehat{\theta_5} \times \overline{Threat\_all} + \widehat{\theta_7} \times \overline{log(distance)} + \widehat{\theta_9}$

[d] $\overline{PTR} = \widehat{\theta_1} + \widehat{\theta_3} \times \overline{N\_airline\_mkt} + \widehat{\theta_5} \times \overline{Threat\_non\_legacy} + \widehat{\theta_7} \times \overline{log(distance)} + \widehat{\theta_9}$

We now consider how market non-stop flight distance affects market airfare by examining the coefficient estimates on the logarithm market distance, $log(distance)$, in each model. Our regression results show that the coefficient estimates are both statistically different from zero with positive signs, suggesting that the longer the market distance, the higher the airfare. Specifically, a 10% increase in market distance between the origin and destination results in approximately 4% increase in equilibrium airfare.

To examine the extent to which market distance affects the size of pass-through,[28] we now look at the coefficient estimate on the interaction term between the logarithm of crude oil price and the logarithm of market distance: $log(P_c) \times log(distance)$. Both coefficient estimates in Model I and II are statistically significant with negative signs, indicating that the size of pass-through declines with longer market distances. For example, everything else constant, a 10% increase in an origin-destination market distance reduces the pass-through elasticity by 0.15% to 0.16%. A 10% increase in market direct flight distance is an increase of approximately 141 miles evaluated at the sample mean of market distance. Guided by the theoretical predictions in **Proposition 4**, the negative sign suggests that, on average, the "*level effect*" dominates the "*elasticity effect*".

A change in crude oil price, which in turn changes gasoline price and the relative cost to consumers of driving versus flying, is likely to shift air travel demand by a larger amount in shorter distance travel as consumers tend to find switching between driving and flying much easier at shorter distances. We refer to as a "*level effect*" in the theoretical analysis, and illustrated in Figure 1.5, a shift in the level of air travel demand induced by changes in crude oil price and the relative

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[28] This impact of market distance on pass-through rate is captured by the parameter θ_7, i.e. $\theta_7 = \frac{\partial PTR}{\partial log(distance)}$ in Model I and II.

cost to consumers of driving versus flying. For example, an increase in crude oil price which increases gasoline price and therefore increases the relative cost of driving versus flying will induce a larger increase in air travel demand in short distance markets compared to long distance markets. The relatively smaller increase in demand in longer distance markets will cause airfare to rise by less in these markets, thus translating into a smaller pass-through of the crude oil price increase to airfare in longer haul markets. In other words, the "*level effect*" implies that the size of pass-through of crude oil price changes to airfare is smaller in longer distance markets.

On the other hand, because demand is likely more elastic in shorter distance markets owing again to consumers greater willingness to switch between driving and flying, optimal price-setting behavior of airlines predicts that airlines are less likely to pass along a cost shock to passengers through airfare in shorter haul markets, an effect we refer to as an "*elasticity effect*" in the theoretical analysis, which is illustrated in Figure 1.6. The "*elasticity effect*" implies the size of pass-through of crude oil price changes to airfare is larger in longer distance markets since demand is less elastic in longer distance markets, which better enables airlines to pass along a cost shock to passengers through airfare. Since the empirical results reveal that the size of pass-through declines with longer market distances, we conclude that on average the "*level effect*" dominates the "*elasticity effect*".

We now examine the potential role of airlines' jet fuel hedging decisions in affecting the equilibrium airfare and the size of pass-through as a result of changes in crude oil price. We first focus on how the $Hedge$ dummy variable may affect the market airfare. In both models, we see positive and statistically significant coefficient estimates on the $Hedge$ dummy variable, suggesting that the average airfare is higher for air travel products offered by airlines that purchase fuel using hedge contracts. Specifically, airfare for air travel products under fuel hedging contracts,

on average is about 43% higher than airfare for air travel products not under fuel hedging contracts. Airlines that use hedging contracts to lock in future fuel purchase price benefit from these hedging contracts during periods of rising fuel prices, but incur a relative cost from being locked into these contracts during periods of declining fuel prices. Figure 1.3 reveals a general decline in fuel prices over the time periods of our sample, which may in part explain the higher average airfare of air travel products offered by airlines locked into hedge contracts during these periods.

To evaluate the impact of the jet fuel hedging contracts on the pass-through rate,[29] we consider the coefficient estimates on the interaction between crude oil price and the hedge dummy variable: $log(P_c) \times Hedge$. The coefficient estimates in Model I and II are both negative and statistically significant at the conventional levels of statistical significance, implying that the adoption of jet fuel hedging contracts places downward pressure on the size of pass-through. Specifically, the pass-through rate for products under fuel hedging contracts, on average, is 0.084 percentage points lower than the pass-through rate for products not bounded by hedging contracts. This result validates our theoretical prediction in **Proposition 2** that fuel hedging provides airlines incentive to reduce the intensity of pass-through to airfare when facing a crude oil price shock. Airlines that enter jet fuel hedging contracts tend to experience smaller changes in their marginal cost from crude oil price shocks compared to airlines that do not use fuel hedging contracts. In this case, the latter airlines are more likely to pass along the crude oil price shocks to consumers through airfare. However, as airline fixed effects are excluded from both regression specifications, we need to be cautious in terms of interpreting the magnitude of the hedging effect. It is possible

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[29] The jet fuel hedging impact on pass-through rate is measured by the parameter θ_9; PTR evaluated at $Hedge = 1$ represents the difference in impact on the pass-through elasticity for products under hedging contracts as opposed to products without hedging.

that the coefficient estimate on *Hedge* dummy variable may capture features other than hedge contracts that are common to all the hedged airlines that differentially influence their cost pass-through rate.

We turn next to analyze how the other factors affect the airfare in the model. The coefficient estimates on *Interstop* in both models are positive and statistically significant at conventional levels of significance. The positive sign implies that each additional intermediate stop that a product has increases average airfare by about 8.4%. Products with more intermediate stops imply longer itinerary flying miles and higher fuel costs associated with the product, which rationalizes the higher airfare for products with more intermediate stops. The same rationale applies to the positive coefficient estimates on the *Inconvenience* variable, a variable that measures flying distance of the itinerary routing relative to the non-stop flying distance between the two endpoints cities.

The sign of the coefficient estimates on $Origin\_Presence$ are both positive and statistically different from zero at conventional levels of statistical significance. Since this coefficient estimate measures airline airport prominence or a "hub premium," we expect the greater the airline presence in an origin airport (thus a larger "hub premium"), the higher the airfare charged by the airline.

Last, to control for the impact of the potential consumer demand on airfare, we introduce the geometric mean of the population size in origin and destination cities in the regression. The coefficient estimates on the logarithm of *Population* are both statistically significant with positive signs in Model I and II, suggesting that the larger the market size, the greater the potential demand and thus the higher is equilibrium airfare.

With the key pass-through parameter estimates in hand, we may assess the overall impact of crude oil price shocks on airline market fare by computing the average rate of pass-through. The last row of Table 1.4 lists the overall pass-through rates using the parameter estimates of $\widehat{\theta_1}, \widehat{\theta_3}, \widehat{\theta_5}, \widehat{\theta_7}, \widehat{\theta_9}$ from the regressions and variables of $N\_airline\_mkt$, $Threat\_all$, $Threat\_non\_legacy$, $distance$ at their sample mean, and the hedging dummy evaluated at 1. Evaluated at the sample mean before considering the hedging effect, the average pass-through rate suggests that, on average, a 10% increase in crude oil price will be translated into a 0.4% to 0.5% increase in airfare. Taking into account the hedging effect, we find that every 10% increase in crude oil price leads to products under hedging being priced relatively lower by approximately 0.35 to 0.44 percentage points. These results do validate the role of jet fuel hedging in mitigating the influence of changes in crude oil price on airfare.

1.5 Conclusion

The primary objective of this paper is to examine the market mechanisms through which crude oil price may influence airfare, which facilitates identifying the possible market and airline-specific characteristics that may influence the extent to which crude oil price changes affect airfare. We first use a simple theoretical model of air travel demand and Nash equilibrium price-setting behavior of airlines to derive clear theoretical predictions that guide proper specification of reduced-form regression models, and help with interpreting empirical results from the regression models. According to our theoretical model, the pass-through from crude oil price changes to changes in airfare is facilitated by demand-side, supply-side, and competitiveness features of origin-destination air travel markets. A key demand-side feature is consumers' willingness to substitute between driving and flying, a key supply-side feature is the extent to which an airline's

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marginal cost is influenced by changes in fuel price, while a key competitiveness feature is the number of airlines providing air travel service in the origin-destination market.

We find that a 10% increase in crude oil price yields a 0.7% increase in an air travel product's fare before considering market and airline-specific factors that influence the pass-through rate. This result provides direct empirical evidence that a given percentage change in crude oil price translates into a certain percentage change in airfare. Consistent with predictions from our theoretical model, we do find evidence that the size of the pass-through of crude oil price changes to airfare depends on several market and airline-specific factors.

First, we find that, on average, each additional carrier actually serving an origin-destination market increases the pass-through elasticity of a typical product in the market by approximately 0.006 percentage points. This is evidence that the size of the pass-through of crude oil price changes to airfare depends on the level of market competition, where market competition is measured by the number of carriers actually serving the market. Specifically, the evidence suggests that the pass-through rate is higher in more competitive markets.

Second, we find that the size of the pass-through of crude oil price changes to airfare not only depends on the level of market competition, but also on the level of potential competition faced by market incumbents. Specifically, our regression results suggest that each additional non-legacy carrier that threatens to enter an origin-destination market raises the pass-through elasticity of a typical product in the market by approximately 0.008 percentage points.

Third, we find that the size of pass-through of crude oil price changes to airfare is smaller in longer distance origin-destination markets. For example, everything else constant, a 10% increase in an origin-destination market distance reduces the pass-through elasticity of a typical product in the market by approximately 0.16%. Our theoretical explanation of this empirical result

is a dominant "*level effect*", which is defined as a shift in the level of air travel demand induced by changes in crude oil price and the relative cost to consumers of driving versus flying. For example, an increase in crude oil price, which increases gasoline price and therefore increases the relative cost of driving versus flying will induce a larger increase in air travel demand in short distance markets compared to long distance markets. The relatively smaller increase in demand in longer distance markets will cause airfare to rise by less in these markets, thus translating into a smaller pass-through of the crude oil price increase to airfare in longer haul markets.

Fourth, we find that airlines' adoption of jet fuel hedging contracts reduces the size of pass-through of crude oil price changes to airfare. Specifically, the pass-through rate for products under fuel hedging contracts, on average, is 0.084 percentage points lower than the pass-through rate for products not bounded by hedging contracts. As shown in our theoretical analysis, hedging contracts effectively reduce the extent to which an airline's marginal cost is influenced by changes in fuel price, which in turn mitigates the influence of fuel price changes on changes in airfare.

A key contribution of this paper is that it provides concrete empirical estimates of the size of pass-through from changes in crude oil price to U.S. domestic air travel market fare, which has not been well studied in the literature. Furthermore, our empirical analysis is built on a theoretical framework that considers both demand and supply side market channels through which changes in crude oil price may be passed through to airfare and onto consumers. To the best of our knowledge, such an analysis of market mechanisms has not been studied by any previous literature that focused on the cost-price pass-through in the airline industry. Relying on a reduced-form regression analysis, however, we are unable to empirically disentangle various demand side and supply side effects on the size of pass-through. As such, future research may want to consider

using a structural econometric model designed to empirically unpack the reduced-form evidence provided in this paper.

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Chapter 2 - How Much Do Consumers Value Single-cup Coffee Brew Technology? Assessing Market Impacts of Single-cup Brew Technology on the U.S. Brew-at-home Coffee Market

2.1 Introduction

New product introduction, which often incorporates new and improved technology, has long played a critical role in influencing not only consumers' tastes and welfare but also firms' profitability and even the overall market structure. According to industry analysts, the single-cup coffee brewing technology has been considered the most-disruptive development in the business since Starbucks Corp began the coffee-shop boom in the late 1980s[30] and even the biggest thing since Luigi Bezzera patented the espresso machine in 1901.[31] K-Cup technology, a single-cup coffee brewing technology pioneered by the American firm Keurig, quickly gained popularity since the late 2000s, driving widespread adoption of the single-cup brewing systems in the United States (US) brew-at-home coffee market.[32] Adoption of the single-cup brewing systems in the US brew-at-home coffee market accelerated further in 2012 when K-Cup patent expired. The rapid rise of single-cup technology fueled sales of single-cup coffee pods. US consumers bought $3.1 billion worth of coffee pods in year 2013 versus $132 million in year 2008.[33] There is little doubt that the introduction of single-cup coffee technology, with a single-serve brewing machine and a

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[30] https://www.theguardian.com/cities/2015/may/14/the-first-starbucks-coffee-shop-seattle-a-history-of-cities-in-50-buildings-day-36

[31] https://en.wikipedia.org/wiki/Espresso_machine

[32] In fact, during the time period when Keurig single-serve systems were widely accepted by the US household, there were many other competitors, such as Salton, Sara Lee and Procter & Gamble, that introduced their own one-cup systems. (https://en.wikipedia.org/wiki/Keurig)

[33] https://www.seattletimes.com/business/single-serve-coffee-revolution-brews-industry-change/

portion-packed coffee pod, has not only changed the way many brew-at-home coffee drinkers brew and consume coffee in daily life, i.e. a change from brewing one "pot" at a time to making one cup at a time, but also altered the overall landscape of the US brew-at-home coffee market.

The key objective of this paper is to examine impacts in the US brew-at-home coffee market associated with the introduction and growing presence of single-cup coffee brewing technology. Specifically, we are interested in measuring changes in prices, consumer demand, firm profitability and overall consumer welfare associated with the introduction and growing presence of single-cup coffee brewing technology.

According to data from Information Resources Inc. (IRI) and Statista, the share of single-cup coffee pods sales among all brewing method coffee types at the retail level rose tremendously from 1.73% in 2008 to 36.5% in 2016, whereas the share of traditional auto-drip brew ground coffee sales experienced a significant decline from over 65% in 2008 to 45.8% in 2016 (See Figure 2.1[34]). What's more, a survey conducted by National Coffee Association (NCA) in 2016 reveals that 28% of the US population reported drinking coffee prepared with single-cup coffee pods in 2016, an increase from 19% in 2012 and 7% in 2011;[35] whereas, in 2016, 50% of the population reported drinking coffee prepared using the traditional auto-drip brewing method, a decline from 70% of the population in 2011, and 61% of the population in 2012 (See Figure 2.2). The fast growth of single-cup coffee sales makes the single-cup technology the second most popular brewing method after the traditional auto-drip technology, far surpassing instant coffee, espresso machines, and all other methods of brewing coffee.

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[34] The category of "Others" includes instant (decaf) coffee, whole bean (decaf) coffee and other coffee substitutes.

[35] The increasing penetration of single-cup coffee consumption in the US households from 2011 to 2012 partially can be explained by the Keurig's K-Cup patent expiration in 2012, leading to an explosion of competitors into the single-cup pods market. (http://time.com/2913062/k-cups-war/)

Figure 2.1 Coffee Retail Sales Share, by Coffee Type
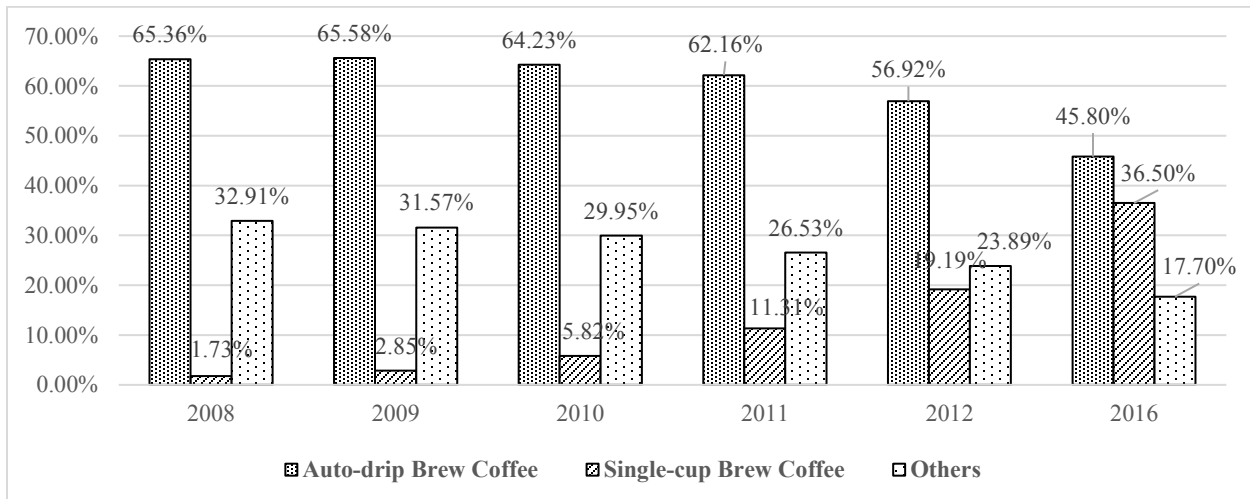
Source: IRI data for 2008 to 2012. Statista.com for 2016.

Figure 2.2 Coffee Preparation Methods Used by the U.S. Households, by Coffee Type
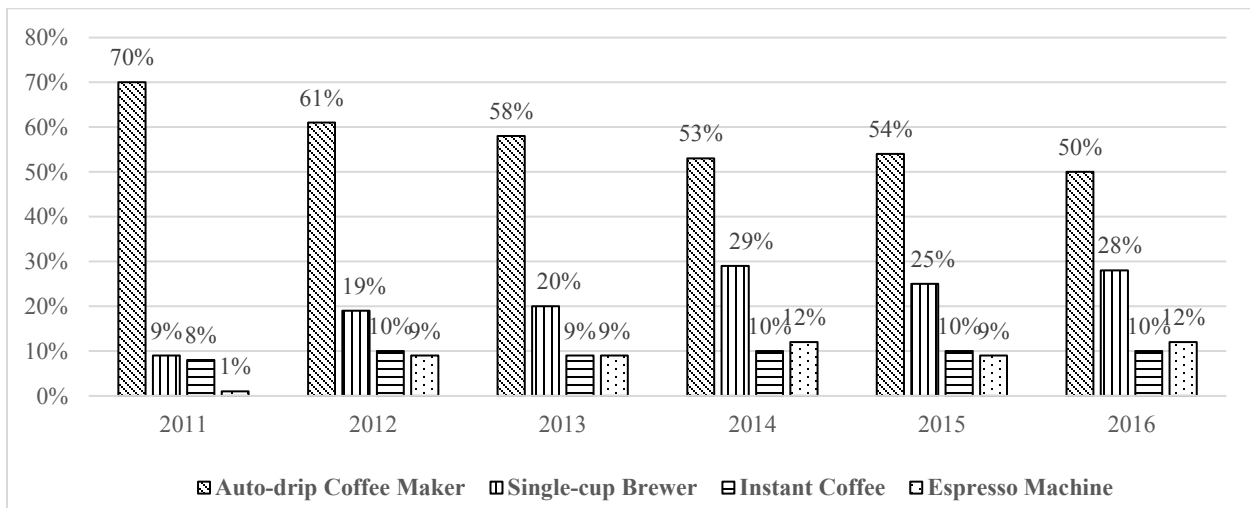
Source: NCA survey (2016)

The analysis in this paper is twofold. First, we examine how much consumers value their coffee consumption experience using the single-cup brewing technology relative to the traditional auto-drip brewing method. Indeed, the paper is motivated by the fact that single-cup brew coffee consumption was soaring since 2012 and substantially cannibalizing the sales of traditional auto-drip brew coffee products. To accomplish the objective of the first part of the analysis we adopt a random coefficients logit demand model [Berry (1994); Berry, Levinsohn, and Pakes (1995); Nevo

(2000a, b, 2001); Petrin (2002) etc.] to obtain estimates of consumers' dollar value willingness to pay (WTP) for the single-cup technology brewing method coffee consumption experience relative to their consumption experience from using traditional auto-drip ground coffee brewing method.

The second part of the analysis is designed to better understand the economic impacts of the single-cup technology brewing method on consumer coffee demand, firm profitability, and consumer welfare. To obtain estimates of firm profitability we specify an oligopoly model based on an assumed strategic price-setting behavior of firms. Specifically, we assume that coffee manufactures set coffee product prices according to a static Nash equilibrium price-setting game. We accomplish the objectives of this part of the analysis by using the estimated coffee demand model along with the specified oligopoly model to perform a counterfactual experiment. The counterfactual experiment asks how equilibrium market outcomes of interest (prices, consumer demand, firm profits, and consumer welfare) are predicted to change if consumers equally value the single-cup technology brewing coffee consumption experience and the traditional auto-drip brewing coffee consumption experience.

Our findings suggest that, on average, a typical coffee drinker is willing to pay up to ¢2.52 extra per equivalent fl oz to consume brewed coffee from the single-cup brewing method and thereby avoid using the traditional auto-drip brewing method. Everything else equal, this WTP estimate implies that, on average, a coffee drinker is willing to pay a price per equivalent fl oz that is 2.57 times the average price per equivalent fl oz of traditional auto-drip brewed coffee products just to enjoy the attribute of single-cup brewing technology as part of the consumption experience instead of the attribute of traditional auto-drip brewing method. Furthermore, our demand model estimates suggest that this relative consumer willingness to pay gap increases with consumer income level, that is, higher income consumers tend to have greater marginal utilities from

consuming coffee with the single-cup brewing technology. Our estimated model reveals that the counterfactual removal of consumer preference for coffee consumption experience with the single-cup brewing technology is predicted to result in an increase in consumer demand for traditional auto-drip brew coffee products and a significant decrease in consumer demand for single-cup brew coffee products. Specifically, such counterfactual preference change is predicted to result in demand for traditional auto-drip brew coffee products at levels that are on average 3.88% greater than the actual demand levels for these products; whereas consumer demand for single-cup brew coffee products decreased by 98.5%. The counterfactual preference change is predicted to result in a typical consumer benefiting from the introduction and growing presence of single-cup brew technology by having a mean increase in individual consumer surplus of 2% from the initial level.

On the supply side, our model estimates suggest that a typical auto-drip brew coffee product has considerably greater margin (price markup over marginal cost as a percent of price) of 55%, compared to the margin of a typical single-cup brew product of 13.6%; whereas the marginal cost for a typical single-cup brew coffee product is about 5 times greater than that of a typical auto-drip brew coffee product. These estimates suggest that single-cup brew coffee products, at least at the early stage of their product life cycle in 2012, are very costly to produce at the margin with relatively small price-cost margins. The counterfactual experiment provides evidence that a typical auto-drip brew ground coffee product in a market is predicted to experience an increase in its variable profit by 4.6% during a month. This predicted impact on variable profit of auto-drip brew coffee products suggests cannibalizing effects associated with the introduction, and growing penetration, of single-cup brewing technology products on traditional auto-drip brew ground coffee products. In other words, a traditional auto-drip ground coffee product could have

had a much greater demand and profitability if consumers did not have a relatively higher preference for new single-cup brewing technology products.

The rest of this paper is organized as follows. Section 2 reviews relevant literature. Section 3 discusses data sources and variables used in the analysis. Section 4 describes the empirical model, as well as the estimation method. Section 5 presents and discusses the empirical results. Section 6 describes the counterfactual procedure and analyzes findings from the counterfactual experiment. Section 7 concludes the paper.

2.2 Related Literature

Previous studies have paid particular attention to traditional auto-drip ground coffee and/or instant coffee categories. A number of studies focus on the response of traditional auto-drip ground coffee prices to input cost shocks (e.g. changes in raw coffee bean price or exchange rates) [Leibtag et al. (2007); Nakamura and Zerom (2010); Bonnet et al. (2013); and Bonnet and Villas-Boas (2016)]. These papers investigate factors that contribute to incomplete pass-through of cost shocks to prices in the coffee market for the traditional auto-drip ground coffee category.[36] Nakamura and Zerom (2010), for example, estimates long-run cost pass-through rates within a dynamic structural framework using retail and wholesale level price data in the US coffee market. Some studies, such as Draganska and Klapper (2007), Draganska, Klapper, and Villas-Boas (2008), Villas-Boas (2007b), and Villas-Boas (2009), focus on vertical relationships between coffee manufacturers and retailers in the traditional auto-drip ground coffee market segment. Villas-Boas (2007b), for example, assesses welfare effects of mergers at the coffee manufacturer level under

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[36] Leibtag et al. (2007) and Nakamura and Zerom (2010) study the ground coffee price-cost pass-through in the US and the other two papers focus on the German ground coffee market.

various assumptions of the vertical structure using retail level scanner data for the traditional auto-drip ground coffee category in Germany. Among studies that focus on vertical relationships between firms in the coffee industry, Noton and Elberg (2016) model bargaining power between coffee manufacturers and retailers in the traditional auto-drip ground and instant coffee categories in Chile.

However, there are only a few research papers studying the single-cup brew coffee category. Chintagunta et al. (2018) study the Portugal coffee market and develop a structural model of demand and supply for the coffee system of single-serve coffee machines and pods as tied-goods. The paper examines the impact of licensing decisions of manufacturers on pricing and profits of firms in the system. Kong et al. (2016) also focuses on coffee brewing machines and pods as tied goods. Their study proposes a static demand system of Keurig single-cup brewing machines and K-Cups partnered with some national coffee brands that are well-known in the mature ground coffee segment, such as Starbucks, Folgers, Maxwell House, etc. The paper performs counterfactual exercises that illustrate the role of partnering and licensing K-Cups with national brands in driving the growth of the overall Keurig single-serve coffee system. Lin (2017) is another similar work that studies the network effect of third-party brands' partnering with K-Cups on the adoption of Keurig brewing systems (the platform) in a two-sided market framework using individual household purchase data. Last, Ellickson et al. (2017) uses a structural model of demand and supply-side bargaining to examine how retailers and manufacturers behave in the absence of private label branded single-serve coffee pods before Keurig patent expired in 2012, and how their strategies adapt when entry occurs after patent expiration in the US single-cup coffee sector.

The above papers focus their empirical analyses uniquely on the single-serve coffee system. Our study, instead, is interested in understanding the potential impact of the growing penetration of single-cup coffee products on traditional auto-drip ground coffee products. Specifically, this paper aims to assess how much consumers value the current quickly growing single-cup market segment relative to the traditional auto-drip ground coffee market segment, and the extent to which key market outcomes of traditional auto-drip ground coffee products, such as demand, prices, and profitability, are impacted by the growing presence of single-cup coffee products. Our research objectives and methodology are related to the literature estimating the economic effects of newly introduced products or technology.

Researchers have studied extensively the economic effects of new products in various industries. A few well-known papers in this literature include Hausman (1996), Hausman and Leonard (2002), Petrin (2002), and Goolsbee and Petrin (2004).[37] The often used research methodology in this literature is to first estimate demand in the presence of the new product, and then use the estimated model to simulate changes in equilibrium market outcomes driven by the counterfactual absence of the new product from consumers' choice set. For example, Petrin (2002) measures the welfare effects of the minivan introduction in the 1980s and finds that consumers overall benefit from the new product introduction. Even though we perform an alternative counterfactual experiment, our research methodology has similarities to the methodology in Petrin (2002). Instead of assessing changes in market outcomes driven by the counterfactual removal of the new product from consumers' choice set as done in Petrin (2002), we assess changes in market

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[37] Hausman (1996) studies the effect of Apple Cinnamon Cheerios. Hausman and Leonard (2002) looks at the effect of Kimberly-Clark bath tissue product 'Kleenex Bath Tissue'. Petrin (2002) focuses on the effect of minivans and Goolsbee and Petrin (2004) on the effect of direct broadcast satellites.

outcomes driven by a counterfactual change in consumers' preference for new products relative to other products in the market. In doing so in our setting, we effectively evaluate the economic effects of changes in consumers' preference for the coffee brewing technology. To the best of our knowledge, this present paper is the first to evaluate the economic importance of consumers' valuation of single-cup coffee brewing technology, and the first to assess the extent to which traditional auto-drip ground coffee product sales and profitability are influenced by the introduction and growing presence of single-cup coffee products.

2.3 Data

The primary data used in our empirical analysis are retail-level scanner data on consumer purchases of traditional auto-drip ground coffee products and single-cup brewing technology coffee products. These scanner data are sourced from the Information Resources Inc. (IRI) academic database [Bronnenberg et al. (2008)], which spans 1795 supermarkets across 50 IRI defined geographical areas in the continental United States. In this study, markets are defined by unique combinations of time periods and IRI defined geographical areas. The IRI defined geographical areas span almost the entire continental US. The data include weekly coffee product unit sales, revenue from these unit sales, and various characteristics of the coffee products. We use data in year 2012.[38] Detailed information for each weekly observation includes: total dollars received by retailers; unit sales of coffee packages; net weight of dry coffee (in ounces) contained in each package, and a set of product attributes. The following product attributes are used to

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[38] Data on single-cup brewing technology coffee products are available from 2008 to 2012. A reason why 2012 is a good year for the analysis we do is that it is the year when single-cup coffee products become the second most popular coffee category according to the 2016 NCA survey. It is thus an important transition year in which the single-cup coffee category started growing quickly in the US.

characterize a product in the present study: coffee type;[39] coffee form;[40] organic information;[41] caffeine content;[42] brewing method;[43] packaging material information;[44] package size information;[45] and promotional information[46]. A product within a market in this study is defined as a unique combination of the retail store where it is sold, the brand name, and all the non-price product attributes listed above. Folgers and Maxwell House are two distinct manufacturers of auto-

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[39] We focus only on two coffee categories: traditional auto-drip technology ground coffee products; and single-cup brewing technology coffee products. All other categories are characterized into "others" including: instant; whole bean; ground decaffeinated; instant decaffeinated; and other coffee substitutes. As you will observe later once we have described the demand model, the "others" category constitutes the "outside" option for consumer choice.

[40] Coffee forms for regular ground coffee include regular grind and fine grind; single-cup coffee products include K-Cups that are trademarked by Keurig, other cups that are compatible with single-serve brewing systems other than Keurig, and single pods that are wrapped with filter papers. (http://www.coffeeteawarehouse.com/coffee-k-cup-vs-pod.html)

[41] All observations due to coding error are removed. Observations with missing organic information are supplemented with information provided by online sources (if they are able to be identified from online resources). All other un-identified observations from any available resources are eliminated.

[42] Caffeine content is approximated using information from USDA National Nutrient Database for Standard Reference Release 27, "Basic Report 14209, Coffee, brewed from grounds, prepared with tap water". On average, 0.61 gram of ground coffee contains 40 mg caffeine, equivalently, 1.86 gram caffeine per ounce of dry coffee.

[43] Brewing methods for all ground coffee are using auto-drip coffee makers, but for single-cup products are either Keurig brewing systems or other one-cup systems such as Nespresso and Tassimo etc. (Euromonitor International).

[44] Product packages for ground coffee including laminated bags (e.g. foil bags or film bags), paper bags/boxes, plastic containers, and light metal tins. (https://plastics.americanchemistry.com/LCI-Summary-for-8-Coffee-Packaging-Systems/)

[45] The package size sometimes refers to the net weight of dry coffee grounds contained in a package. It is difficult to use this information when defining a product as this measure has nearly continuous values across all records in the data. Some records have small decimal differences in this measure. For example, two auto-drip coffee products owned by CHOCK FULL O NUTS sold in January-Boston market are in 10.3008 oz package and 10.5008 oz package, respectively; and all other product attributes of these two products are the same. Therefore, following the large package definition in Guadagni and Little (1998) and Ansari, Bawa, and Ghosh (1995), we categorize the packages sizes into two discrete categories: Large or Small. Large packages contain dry coffee grounds greater than 16 oz, while small packages contain up to 16 oz of dry coffee grounds.

[46] These data contain information related to promotional activities such as feature, display, and temporary price cut.

drip coffee products and single-cup coffee products. An example of an auto-drip coffee product sold in the January-Atlanta market, where January identifies the specific month during year 2012, and Atlanta identifies the relevant geographic area, is: Folgers' auto-drip, regular ground, non-organic, caffeine content of 0.93 gram of caffeine per ounce of dry coffee, packed in large bulk size in a plastic canister (29.2 oz), sold without any promotions in the retail store that have ID number "242546". Similarly, an example of a single-cup coffee product sold in the same January-Atlanta market is: Maxwell House's single-cup coffee, non-organic, caffeine content of 1.86 gram of caffeine per ounce of dry coffee, packed in individual single cups with 16 cups in the laminated bag (4.45 oz), sold without any promotions in the retail store that have ID number "242546". These weekly observations are aggregated to monthly data based on defined products and markets. The monthly aggregation reduces the 10 million weekly observations to 1.4 million monthly observations. With 12 months and 50 IRI defined geographic areas, we have 600 markets in total.

2.3.1 Construction of Price and Quantity Variables

To prepare the dataset for the empirical analysis, we create the price and quantity variables for defined products. To analyze consumer taste variation across single-cup brew and traditional auto-drip brew ground coffee products, we need a comparable quantity measure. Previous literature studying the coffee market focus on traditional auto-drip brew ground coffee and/or instant coffee products, and the measure of coffee demand/consumption is universally in terms of mass weight of dry coffee grounds in ounces[47] [Villas-Boas (2007a, 2007b), Leibtag et al. (2007),

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[47] There are several exceptions that focus on the single-cup coffee market. For example, Ellickson et al. (2017) adopt a similar conversion method as in our paper. Chintagunta et al. (2018) focus uniquely on single-cup coffee, thus the price variable measures the per pod price.

Nakamura and Zerom (2010), Bonnet et al. (2013), Bonnet and Villas-Boas (2016)]. However, the demand for single-cup brew coffee pods, given their distinct brewing method from the traditional auto-drip ground coffee, cannot be simply measured by the mass weight of dry coffee grounds contained in coffee pods.

In order to construct prices that are comparable across the two coffee segments, we first define an equivalent serving size for each segment, namely, the mass weight of coffee grounds in ounces (oz) to make a standard cup of brewed coffee, 10 fluid ounces (fl oz). This standard cup size is a product of the NCA survey in 2016.[48] For single-cup coffee products in our data, an individual coffee pod contains coffee grounds of $0.3 - 0.4$ oz varying by brands, with an average of 0.35 oz in a typical coffee pod. We assume each pod makes a standard cup of 10 fl oz of freshly brewed coffee regardless of how much coffee grounds each pod contains. For traditional auto-drip brew coffee products, we apply a universal serving size of 0.317 oz coffee grounds per standard 10 fl oz cup of coffee.[49] Given these assumptions, we convert the product quantity measured in ounces of dry coffee grounds in the original IRI data to equivalent fluid ounce measure across traditional auto-drip brew coffee products and single-cup brew coffee products. Therefore, consumer quantity demanded is measured by how much fluid ounces of brewed coffee can be potentially made from each product given the product's equivalent serving size.

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[48] This survey also reports that the average number of cups drank per-day per capita is 1.98. This implies a coffee drinker consumes 594 fl oz per month, on average.

[49] The coffee-to-water ratio suggested by NCA is one to two tablespoons of ground coffee for every six fluid ounces of water. (http://www.ncausa.org/About-Coffee/How-to-Brew-Coffee) The two largest ground coffee brands, Folgers and Maxwell House, both suggest a recipe of one tablespoon ground coffee (about 0.19 ounces) per six fluid ounces of water for regular strength, and two tablespoon ground coffee (about 0.38 ounces) per six fluid ounces of water for strong coffee. (https://www.folgerscoffee.com/coffee-how-to/how-to-measure-coffee) We consider an average coffee drinker follows a regular strength brewed coffee recipe, i.e. 0.0317 oz ground coffee makes 1 fl oz brewed coffee. Using this ratio, we then compute the total fluid ounces for each ground coffee product.

For each weekly observation in the data, we have information on total dollars received by the retailer for multiple packages sold during a week, the number of packages as well as the net weight (in ounces) of coffee grounds in a package. Before collapsing the weekly data to monthly, we compute the total quantity sold in equivalent fluid ounces for each weekly observation of single-cup brew products by multiplying the number of pods in a package with the number of packages sold in a week and then multiply by the standard cup size of 10 fl oz. For traditional auto-drip brew coffee products, we first compute the total ounces of ground coffee sold in each week by multiplying the net weight of coffee grounds in a package with the number of packages sold in a week. Assuming a typical consumer utilizes a typical coffee-water ratio of "0.317 oz/10 fl oz" to make a "pot" of brewed ground coffee, we compute the total quantity sold in equivalent fluid ounces in a week by dividing the total ounces of coffee grounds sold by this ratio. We then calculate the weekly average price for each weekly product observation using the ratio of total dollars from sales to total equivalent fluid ounces sold in a week. When collapsing the data to monthly frequency, the "price" variable for a product is the mean of those weekly average prices for a product sold during a month, and the "quantity" variable for a product is the sum of total equivalent fluid ounces sold in a month.

Within the framework of a discrete choice demand model, to calculate the market share of each product in a market that allows for outside goods option, one needs a measure of potential market size that is larger than the actual aggregate consumption of products in the market. Potential market size (later denoted M_t) is computed as the total equivalent fluid ounces of brewed coffee that could be consumed in a market during a month if all adult males and females in the market consumed coffee at the typical per capita consumption rates for males and females

respectively.[50] The observed product share (later denoted S_{jt}) is computed by dividing the quantity sold of a product in equivalent fluid ounces by the above defined potential market size, while the share of the outside goods option, denoted as S_{0t}, is computed as $S_{0t} = 1 - \sum_{j \epsilon J} S_{jt}$, where J represents the set of coffee products in market t of our data. The outside good share is a measure of the proportion of the potential market size who did not consume any of the J coffee products in market t.

The summary statistics of price, quantity, and market size are presented in Table 2.1. In the collapsed dataset, a given market, on average, contains 2,324 products, and the data contain 600 markets according to our product and market definitions. There are 1,394,455 observations in the data. These coffee products sold in year 2012 have an average coffee price of ¢2.93 per equivalent fl oz, with a mean monthly quantity sold in a market of 10,982 equivalent fl oz. The table also reveals that coffee products that require using the single-cup brewing technology are on average more expensive than traditional auto-drip brew coffee products. In particular, mean product price among single-cup brewing technology coffee products is ¢6.40 per equivalent fl oz, while mean product price among traditional auto-drip brewing method coffee products is ¢1.61 per equivalent fl oz. Last, the measure of potential market sizes described above yields a mean of product shares equal to 8.82E-06.

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[50] Based on the NCA survey, we calculate the total equivalent fluid ounces of brewed coffee consumed by a female and a male per month respectively. On average, a female drinks 1.85 cups per day and a male drinks 2.11 cups per day, with each standard cup being 10 fl oz. The female and male adult populations in a market are obtained from the American Community Survey estimates in 2012.
(https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_15_5YR_DP05&src=pt)

2.3.2 Other Variables

Other variables that characterize product attributes are reported in Table 2.1. To evaluate consumer preference for the coffee brewing technology consumption experience, we include a coffee type dummy variable, *Single-cup Brew*. Dummy variable, *Single-cup Brew*, equals to 1 if a coffee product is designed to use the single-cup brewing technology, and 0 if the product is designed to use the traditional auto-drip brewing technology. On average, 27.5% of products in our data set are single-cup brew coffee products, while the other products in our data set are traditional auto-drip brew coffee products.

Consumers normally show varying tastes between organic and non-organic food and beverage items. To capture the potential impact that the organic feature of coffee products has on consumer demand, we consider a dummy variable, *Organic*, equal to 1 if a product is organic coffee and 0 otherwise. As Table 2.1 reveals, most coffee products in the data sample are non-organic.

Many studies analyze the extent to which marketing strategies used by retailers, such as whether the product is featured in the retail store, specially displayed in the retail store, and/or have a temporary retail price cut, affect consumer brand choice and brand loyalty [Hwang and Thomadsen (2017), Bronnenberg et al. (2012) and Boatwright, Dhar and Rossi (2004)]. To capture the potential impact of retailer marketing activities on consumer demand, we construct a variable, *Deal_cnt*, which counts the number of weeks in a month that a product is on feature, display, or has a temporary price cut. The summary statistics in Table 2.1 shows that on average, the typical product is promoted 0.84 weeks within a month.[51] We expect a positive effect of promotional activities on consumer demand.

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[51] Coffee is one of the most frequently promoted consumer packaged goods (CPGs) (Boatwright et al. (2004)).

Table 2.1 Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Price ($/fl oz across all coffee product types)	0.029	0.024	9.04E-06	0.179
Price ($/fl oz across traditional auto-drip brew coffee products)	0.016	0.007	9.04E-06	0.114
Price ($/fl oz across single-cup brew coffee products)	0.064	0.019	0.000082	0.179
Quantity (fl oz)	10982	31226	39.42	2510784
Single-cup Brew dummy (Single-cup brew coffee products = 1)	0.275	0.447	0	1
Organic dummy (organic coffee products = 1)	0.063	0.243	0	1
Deal_cnt (No. of weeks per month a product was promoted)	0.846	1.154	0	5
Caffeine (gram per ounce)	1.685	0.477	0	2.23
Large package dummy (>16 ounces in a package=1)	0.205	0.404	0	1
Product market shares (all inside goods)	8.82E-06	0.00009	4.60E-09	0.035
Market shares of outside goods	0.982	0.014	0.738	0.997
No. of defined products in a market	2324	1945.15	193	12045
No. of defined markets	600			
IRI geographical areas	50			
No. of retailers	1,795			
No. of manufacturers	240			
No. of brands	317			
No. of observations	1,394,455			

* All prices are adjusted to 2012 dollars.

The caffeine content for a typical product is 1.68 grams per ounce with a minimum of 0 for a decaffeinated coffee product. Caffeine is a major pharmacologically active compound in coffee beans, and it is a mild central nervous system stimulant [de Mejia and Ramirez-Mares (2014)]. Coffee, like other caffeinated soft drinks, acts as a stimulant beverage. As such, we expect a positive impact of caffeine content on consumer demand.

Last, we consider the demand impact of package size, which is captured by dummy variable, *Large*, equal to 1 if a product has a net weight of coffee grounds in a package greater than the standard package size of 16 oz [Guadagni and Little (1998); and Ansari, Bawa, and Ghosh (1995)], 0 otherwise. The demand model coefficient estimate on dummy variable, *Large*, is expected to be positive according to the similar estimate in previous literature.

There are 240 coffee manufacturers and 317 brands in the data sample. It will be too large of a table to report summary statistics by all coffee manufacturers. Therefore, for the data reported in Table 2.2, we select ten coffee manufacturers that have the largest shares of total revenue during the sample period. In the table, we also include a firm that is the only firm in the data that solely produces single-cup coffee, TREEHOUSE FOODS INC. Table 2.2 presents summary revenue information of eleven firms. We distinguish the type of firms based on whether a firm produces both traditional auto-drip brew coffee products and single-cup brew coffee products or only one of the two coffee categories. Among these firms, there are six, defined as multi-coffee-type-product firms, that produce both traditional auto-drip brew coffee products and single-cup brew pods. The largest multi-coffee-type-product firm is THE JM SMUCKER CO, with the largest total coffee revenue share of 30.58% during 2012. This firm also has the largest dollar sales of auto-drip brew coffee products, accounting for 34.02% of total dollar sales of all auto-drip brew coffee products across all firms during the sample period. KEURIG GREEN MOUNTAIN is the second largest multi-coffee-type-product firm in terms of total coffee dollar sales, with 19.02% total coffee sales and the largest single-cup brew coffee producer, with single-cup pods dollar sales of 71.55% among single-cup pods revenue across all firms during 2012.

Table 2.2 A Sample of Coffee Manufacturers with Annual Revenue Share > 1% in 2012

		All Products		Auto-drip Brew Coffee Products		Single-cup Brew Coffee Products	
		$	%	$	%	$	%
Multi-coffee-type-product Firms	THE J M SMUCKER CO	72,700,000	30.58%	60,900,000	34.02%	11,800,000	20.10%
	KEURIG GREEN MOUNTAIN	45,200,000	19.02%	3,139,717	1.75%	42,000,000	71.55%
	KRAFT FOODS GROUP INC	34,800,000	14.64%	33,700,000	18.83%	1,046,781	1.78%
	PRIVATE LABEL	24,100,000	10.14%	22,400,000	12.51%	1,668,879	2.84%
	STARBUCKS COFFEE CO	19,700,000	8.29%	19,600,000	10.95%	80,215	0.14%
	THE REILY COMPANIES	4,257,153	1.79%	4,236,401	2.37%	20,752	0.04%
Single-coffee-type-product Firms	MASSIMO ZANETTI BEVERAGE USA	8,022,678	3.38%	8,022,678	4.48%		
	JOH A BENCKISER (JAB)	6,867,266	2.89%	6,867,266	3.84%		
	TATA TEA LTD	4,719,001	1.99%	4,719,001	2.64%		
	F GAVINA & SONS INC	2,438,692	1.03%	2,438,692	1.36%		
	TREEHOUSE FOODS INC	336,113	0.14%			336,113	0.57%
Total Coffee $ Sales in 2012		**$ 237,700,000**		**$ 179,000,000**		**$ 58,700,000**	

2.4 The Model

In this section, we outline the analytical framework used to perform the empirical analysis. The analytical framework is to estimate structural parameters that govern US domestic brew-at-home coffee markets demand and supply, and then use the estimated structural parameters to simulate new market equilibrium outcomes based on specific assumed counterfactual changes. The counterfactual change we analyze is to assume that consumers are indifferent between coffee consumption with the single-cup brewing technology and with the traditional auto-drip brewing technology.

Our empirical procedure contains two steps. First, we specify and estimate a random coefficients logit demand model that allows consumers' heterogeneous preferences to affect coffee demand [see, e.g., McFadden (1984), Berry (1994), Berry, Levinsohn and Pakes (1995), Nevo (2000a, b, 2001), Petrin (2002) and many others]. Particularly, we follow the method described in Nevo (2000a) and Berry, Levinsohn and Pakes (1995) that uses market-level price and quantity data for each product in a series of markets to estimate the demand model, taking into account that product prices are likely correlated with shocks to demand embodied in the demand error term. Compared to standard logit and nested logit demand models, the random coefficients logit model allows for considerable flexibility in the specification of heterogeneous consumer preferences and potentially yield consumer substitution patterns across products that are difficult, and sometimes impossible, to obtain from the standard logit or nested logit models. Of particular interest are estimates of demand parameters that capture consumers' relative taste preference for their coffee consumption experience with the single-cup brewing technology compared to their coffee consumption experience with the traditional auto-drip brewing technology.

The second step of the empirical procedure requires specification of an oligopolistic model of competition between firms that supply coffee products. The oligopolistic model we use assumes coffee firms set coffee product prices according to a static Nash equilibrium price-setting game. Optimal price-setting behavior of firms in the oligopoly model implies a set of equations that depend on demand parameter estimates and allows us to compute product-level markups and recover estimates of product-level marginal costs. With the product-level marginal costs in hand along with demand parameter estimates, we again use the optimal price-setting behavioral equations implied by the oligopoly model to perform a counterfactual experiment. The counterfactual experiment asks how equilibrium market outcomes of interest (prices, consumer demand, firm profits, and consumer welfare) are predicted to change if consumers equally value the single-cup technology brewing coffee consumption experience and the traditional auto-drip brewing coffee consumption experience. Operationalizing the counterfactual experiment simply requires us setting to zero estimates of demand parameters that capture consumers' relative taste preference for their coffee consumption experience with the single-cup brewing technology compared to their coffee consumption experience with the traditional auto-drip brewing technology. Since these demand parameters are embedded into the optimizing equations implied by the oligopoly model, we simply use these equations to facilitate computation of new counterfactual market equilibrium outcomes of interest.

2.4.1 Demand

We model consumers' coffee product choices with a random utility discrete choice model. Suppose there are T distinct markets for coffee products, and markets are indexed by $t = 1, ..., T$. Each market is populated with I_t potential coffee consumers, and consumers are indexed by $i =$

$1, \dots, I_t$. Consumers in each market are faced with J_t distinct coffee product choices, in addition to the alternative of not to purchase one of the J_t distinct coffee products in our data sample. Therefore, in each market consumers are effectively faced with $J_t + 1$ alternatives, which are indexed by $j = 0, \dots, J_t$, where $j = 0$ represents consumers' outside option of not purchasing one of the coffee products in our data sample. In our analysis, consumers' outside option is a composite of several possibilities such as buying other coffee substitutes (e.g. instant coffee, whole bean coffee, ready-to-drink coffee beverages, etc.) or simply not buying.

The conditional indirect utility consumer i obtains from choosing product j in market t is:

$$U_{ijt} = x_{jt}\beta_i + \phi_i Single - Cup\ Brew_{jt} + \alpha_i p_{jt} + a_t + a_s + a_b + \xi_{jt} + \varepsilon_{ijt} \qquad (2.1)$$

where x_{jt} is a vector of K observed product characteristics that vary across products and markets; and β_i is a $K + 1$ vector of consumer-specific taste parameters i.e., marginal utilities, associated with the corresponding product characteristic variables in x_{jt}. $Single - Cup\ Brew_{jt}$ is a zero-one dummy variable that equals to one only if consumption of coffee product j in market t requires using single-cup brewing technology; and ϕ_i is the associated consumer-specific taste parameter. Since consumption of the coffee products in our data sample either requires using traditional auto-drip brewing technology, or using single-cup brewing technology, this implies that parameter ϕ_i measures consumer $i's$ preference for the single-cup brewing technology consumption experience compared to the traditional auto-drip brewing technology consumption experience. p_{jt} is the price of product j in market t, assumed common to all consumers; and α_i is the consumer-specific taste parameter that measures the consumer's marginal utility of price. a_t captures market-specific shocks to consumers' preferences for coffee products; a_s captures retail store-specific shocks to consumers' preferences for coffee products; and a_b captures brand-specific differences in consumers' preferences for coffee products. In estimation, we control for

fixed effects captured by a_t, a_s, and a_b using relevant zero-one dummy variables. Finally, ξ_{jt} is a composite of product characteristics that are observed by consumers and firms, but unobserved by us the researchers; and ε_{ijt} is a mean-zero stochastic error term.

The distribution of consumers' taste parameters, β_i, ϕ_i and α_i, is specified as:

$$\begin{pmatrix} \beta_i \\ \phi_i \\ \alpha_i \end{pmatrix} = \begin{pmatrix} \beta \\ \phi \\ \alpha \end{pmatrix} + \Gamma D_i + \Sigma v_i, \quad v_i \sim N(0, I_{K+3}) \tag{2.2}$$

where D_i is a $m \times 1$ vector of observed consumer demographic variables with mean of zero and variance of one across all markets; and Γ is a $(K + 3) \times m$ matrix of parameters that measures how consumers' taste for attributes of coffee products vary by observed demographics. In the actual demand estimation, we include income in D_i in the form of deviation from its market mean, to allow an individual's marginal utility of specific product attributes to vary with his or her income level. Unobserved shocks to consumers' taste for various product attributes are contained in v_i, which is assumed to follow a standard normal distribution. Σ is a diagonal matrix, where the elements on the main diagonal are parameters which measure variation in taste across consumers for various product attributes. Given the zero mean of elements in v_i and D_i, the vector of parameters $\begin{pmatrix} \beta \\ \phi \\ \alpha \end{pmatrix}$, measures the mean of the random coefficients.

Based on equations (1) and (2) above, the conditional indirect utility consumer i obtains from the purchase of product j in market t can be re-written as:

$$U_{ijt} = \delta_{jt}\left(x_{jt}, Single - Cup\ Brew_{jt}, p_{jt}, a_t, a_s, a_b, \xi_{jt}; \beta, \phi, \alpha\right)$$

$$+\mu_{ijt}\left(x_{jt}, Single - Cup\ Brew_{jt}, p_{jt}, D_i, v_i; \Gamma, \Sigma\right) + \varepsilon_{ijt} \tag{2.3}$$

where $\delta_{jt} = x_{jt}\beta + \phi Single - Cup\ Brew_{jt} + \alpha p_{jt} + a_t + a_s + a_b + \xi_{jt}$ is the mean utility (across consumers) obtained from consuming product j; and $\mu_{ijt} = [x_{jt}, Single -$

$Cup\ Brew_{jt}, p_{jt}](\Gamma D_i + \Sigma v_i)$ is a consumer-specific deviation from the mean utility level. The outside option, denoted good 0, yields mean utility that is normalized to be zero. For computational tractability, the idiosyncratic error term ε_{ijt} is assumed to be governed by an independent and identically distributed extreme value density. [52] The probability that product j is chosen, or equivalently the *predicted* (by the model) market share of product j is therefore:

$$s_{jt}(x_{jt}, p_{jt}, \xi_{jt}; \beta, \phi, \alpha, \Gamma, \Sigma) = \int \frac{e^{\delta_{jt} + \mu_{ijt}}}{1 + \sum_{l=1}^{J} e^{\delta_{lt} + \mu_{ilt}}} d\widehat{F(D)} dF(v) \tag{2.4}$$

where $\widehat{F(D)}$ and $F(v)$ are population distribution functions for consumer demographics and random taste shocks assumed to be independently distributed. As is well-known in the empirical industrial organization literature, there is no closed-form solution for the integral in equation (4), and thus it must be approximated numerically using random draws from $\widehat{F(D)}$ and $F(v)$.[53]

Finally, the demand for product j is given by:

$$d_{jt} = M_t \times s_{jt}(x_{jt}, p_{jt}, \xi_{jt}; \beta, \phi, \alpha, \Gamma, \Sigma) \tag{2.5}$$

where M_t is a measure of the potential size of market t; $s_{jt}(x_{jt}, p_{jt}, \xi_{jt}; \beta, \phi, \alpha, \Gamma, \Sigma)$ is the predicted product share function from equation (4); and $(\beta, \phi, \alpha, \Gamma, \Sigma)$ is the set of demand parameters to be estimated. The potential market size measure M_t, as previously described, is the total equivalent fluid ounces of brewed coffee that could be consumed in a market during a month if all adult males and females in the market consumed coffee at the typical per capita consumption rates for males and females respectively.

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[52] For notational convenience, from this point onwards we let x_{jt} represents all the measured non-price product characteristics in our data, including variable, $Single - cup\ Brew_{jt}$.

[53] In the actual demand estimation, we use 200 random draws from $F(\cdot)$ for the numerical approximation of $s_{jt}(\cdot)$.

2.4.2 Supply

The supply side of our structural econometric model can be designed to capture both the horizontal and vertical relationships between coffee manufacturers and retailers [Bonnet and Dubois (2010); Bonnet et.al. (2013); and Bonnet and Villas-Boas (2016)]. However, in this paper, it is not our focus to explore which supply model best represents the vertical structure of the US coffee industry. Instead, we make the simplifying assumption that retailers do not play a strategic role in setting retail prices of the coffee products in our analysis, and simply set retail prices just high enough to cover their economic retailing costs and costs to obtain coffee products from coffee manufacturers. We do assume coffee manufacturers play a strategic role in setting prices of their coffee products to non-cooperatively maximize firm-level profit. As such, we consider a supply model of the coffee industry in which coffee manufacturers effectively determine coffee product prices according to a static Nash equilibrium price-setting game.

Suppose each coffee manufacturer f offers a set of coffee products in market t, F_{ft}, and sets the prices of these products to maximize the firm's variable profit:

$$\max_{p_{jt} \forall j \in F_{ft}} VP_{ft} = \max_{p_{jt} \forall j \in F_{ft}} \sum_{j \in F_{ft}} (p_{jt} - mc_{jt}) q_{jt}$$

$$= \max_{p_{jt} \forall j \in F_{ft}} \sum_{j \in F_{ft}} (p_{jt} - mc_{jt}) \times M_t \times s_{jt}(\boldsymbol{p}) \tag{2.6}$$

where in equilibrium the quantity of coffee product j that gets sold in market t, q_{jt}, is exactly equal to the market demand of this product, i.e. $q_{jt} = M_t \times s_{jt}(\boldsymbol{p})$. Recall that M_t is a measure of potential market size; $s_{jt}(\boldsymbol{p})$ is the *predicted* market share function for product j; and $\boldsymbol{p}$ is a vector of the prices for the J products in market t. Last, mc_{jt} represents the marginal cost incurred by the firm to provide product j in market t.

The first-order conditions generated from the optimization problem in equation (6) for all competing firms are a set of J equations, one for each product. Following expositions in Nevo (2000a), the set of J first-order conditions imply the following product markup equation expressed in matrix notation:

$$p - mc = -(\Omega * \Delta)^{-1} \times s(p) \tag{2.7}$$

where $s(\cdot), p, mc$ are $J \times 1$ vectors of product shares, prices, and marginal costs, respectively; Ω is a $J \times J$ matrix of appropriately positioned zeros and ones based on the manufacturers' ownership structure of the J products; Δ is a $J \times J$ matrix of first-order derivatives of predicted product shares with respect to prices; and $\Omega * \Delta$ is an element-by-element multiplication of the two matrices.

Equation (7) above implies product-level markup estimates, i.e. $mkup(x, p, \xi; \hat{\beta}, \hat{\phi}, \hat{\alpha}, \hat{\Gamma}, \hat{\Sigma}) = -(\Omega * \Delta)^{-1} \times s(p)$, which depend exclusively on the demand-side variables and parameter estimates. Using computed product-level markups and product prices, product-level marginal cost estimates can be recovered as follows:

$$\widehat{mc} = p - [-(\Omega * \Delta)^{-1} s(p)] \tag{2.8}$$

Last, with the estimated markups given by equation (7), manufacturers' variable profits can be computed using:

$$\widehat{VP}_{jt} = \sum_{j \in F_{ft}} mkup_{jt}(x, p, \xi; \hat{\beta}, \hat{\phi}, \hat{\alpha}, \hat{\Gamma}, \hat{\Sigma}) \times M_t \times s_{jt}(x, p, \xi; \hat{\beta}, \hat{\phi}, \hat{\alpha}, \hat{\Gamma}, \hat{\Sigma}) \tag{2.9}$$

2.4.3 Estimation and Identification of Demand

To estimate the set of demand parameters, we use generalized method of moments (GMM) following the previous literature [Berry (1994), Berry, Levinsohn and Pakes (1995), Nevo (2000a)

and Petrin (2002)]. The general strategy is to derive parameter estimates such that the *observed* product shares S_{jt} are equal to the *predicted* product shares s_{jt}.[54]

Instruments

The classic econometric problem in logit demand estimation is the endogeneity of prices. Obtaining consistent demand parameter estimates relies heavily on the selection of instrument variables for the endogenous product prices. Consumers make purchase decisions among different coffee products, where a product is perceived as a bundle of product attributes. Product attributes unobserved by researchers, which are contained in ξ_{jt}, are likely correlated with prices. Hence, it is important to select appropriate instrument variables for prices. One way to cope with the endogeneity of prices is to account for fixed differences in ξ_{jt} in a flexible manner by introducing dummy variables [Nevo (2001)]. These dummies control for constant differences in consumer utility across products as well as regional differences in the mean utility of products. As such, to help mitigate the endogeneity problem we include in the mean utility function time dummies, store dummies, brand dummies, and geographic region dummies (i.e. IRI geographical areas) to account for some product characteristics in ξ_{jt}.

To further mitigate the endogeneity problem, we construct instruments for products prices using direct components of marginal cost interacted with brand fixed effects as in Villas-Boas (2007a, 2007b) and Nakamura and Zerom (2010). Firms set coffee product prices by taking into

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[54] The predicted product share integral is approximated by using the following simulator given by: $s_{jt} = \frac{1}{ns}\sum_{i}^{ns}\frac{e^{\delta_{jt}+[x_{jt},p_{jt}](\Gamma D_i+\Sigma v_i)}}{1+\sum_{l}^{J}e^{\delta_{lt}+[x_{lt},p_{lt}](\Gamma D_i+\Sigma v_i)}}$, where ns is the number of random draws from the distribution of D and v; $ns = 200$ in the actual demand estimation. The 200 individual draws are obtained from Public Use Microdata Sample (PUMS) datasets.

account exogenous cost-side variables, such as coffee bean prices, energy prices, and exchange rates. Due to the exogeneity of these input markets from the perspective of coffee markets, it is likely that these input prices are uncorrelated with shocks to coffee demand contained in ξ_{jt}. For example, a firm's changes how coffee products are displayed in a store, which likely influence demand and prices for its products due to such changes being captured in ξ_{jt}, are unlikely to be correlated with exchange rate changes between Brazil and the U.S. However, exchange rate changes between Brazil and US are likely to influence the prices of several coffee products.

When estimating demand, we include three types of instruments for prices. The first is time-varying exchange rates between Brazilian real and US dollar interacted with brand dummies.[55] Raw coffee beans, like any other exchange-traded commodities, are traded in commodity exchange markets, such as the New York Stock Exchange (NYSE). Changes in exchange rates often impact raw coffee bean trade flows and trading prices. The largest raw coffee bean exporting country is Brazil, which is also the main source of coffee bean imports for the US coffee industry in 2012, according to International Coffee Organization (ICO).[56] Therefore, changes in exchange rates between Brazil real and US dollar are likely important in explaining variations in coffee products' production costs. By using the interactions between exchange rates and brand dummies as instrument variables, we allow exchange rates to influence coffee products' production costs differently across brands. As in Nakamura and Zerom (2010), we consider lagged exchange rates to capture the potential lagged response in coffee products' production costs and its transmission to influence coffee product prices.

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[55] Exchange rate between Brazil and US is obtained from the website of the Federal Reserve Bank of St. Louis. (https://fred.stlouisfed.org/series/DEXBZUS)

[56] Global coffee trade statistics can be found at the ICO website: http://www.ico.org/new_historical.asp

For the second set of instruments, we interact the national average electricity prices[57] with the dummy variables for four different packaging materials for coffee products. The packaging materials are: (1) paper bags/boxes; (2) laminated (foil) bags; (3) plastic canisters; and (4) light metal tins. By interacting electricity price with zero-one dummy variables that correspond to the four different packaging materials, we allow these four instrument variables to capture the likelihood that changes in electricity prices affect coffee products' production costs differently across different packaging processes. Furthermore, in principle this set of instruments is valid since changes in electricity price are unlikely to be driven by changes in coffee markets, making this set of instruments exogenous to coffee markets.

Last, we include the mean of *Deal_cnt* across all products for each coffee producer as an additional instrument for product price. The first-order conditions associated with firms' optimal choice of prices to maximize their variable profit reveal that a product's equilibrium price is a function of markup and marginal cost. As such, a change in a product's markup is likely to affect its price. The idea is that the average markup that a producer is able to charge is related to the characteristics of its products.

2.5 Empirical Results

2.5.1 Demand

The demand model estimates can be found in Table 2.3. The first column reports parameter estimates from the standard logit model using the ordinary least squares (OLS) estimator without

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[57]Electricity price is from the US Energy Information Administration (EIA) website: (https://www.eia.gov/electricity/data/browser/#/topic/7?agg=0,1&geo=00fvvvvvvvvvo&endsec=vg&freq=M&start=201201&end=201212&ctype=linechart&ltype=pin&rtype=s&pin=&rse=0&maptype=0)

instrumenting for price; the second column reports standard logit model parameter estimates where we have instrumented for prices using the set of instrument variables discussed in the previous section. Parameter estimates from the random coefficients logit demand model are reported in the last three columns. In the last three columns of estimates, consumer heterogeneity is considered by allowing the coefficient on coffee product price and other product characteristics to vary across individual consumers.

Comparing OLS estimates, which are obtained without using instruments for price, with the other columns of estimates (two-stage least squares (2SLS) and generalized method of moments (GMM)) when price instruments are used, one notices that the coefficient estimate for price increases in absolute value with instrumentation. As stated in the model section, price is an endogenous variable that is likely correlated with product attributes in ξ_{jt} since these product attributes are observed by decision-making consumers and firms, even though they are not observed by us the researchers. The Wu-Hausman endogeneity test statistics of 33392.11 confirms the endogeneity of price by rejecting the exogeneity of price at 1% level. It suggests that the OLS estimation produces biased and inconsistent estimates of the price coefficient. Moreover, the weak instrument test using Stock and Yogo's (2005) test yields a test statistic of 112.22, which is statistically significant at 1% level, and thus rejects the null hypothesis that the instruments used for price are weak. We focus the remainder of our analysis on demand estimates obtained from the random coefficients model.

Among the last three columns, the first column of estimates reports means of the distribution of marginal utilities ($\beta's$). The second column of estimates labeled "Standard Deviations" measures taste variation of select product attributes driven by unobserved consumer

characteristics, v_i. The last column of estimates represents the effect of consumer income on consumers' marginal utilities of select product attributes.

We find the mean coefficient estimate for price is negative and statistically significant at 1% level, indicating coffee price, on average, has a negative impact on consumers' mean utility. All else equal, an increase in a product's price reduces the probability that a typical coffee drinker chooses the product. The coefficient estimate on the interaction between price and consumer income level is statistically significant at conventional levels of statistical significance. The positive coefficient estimate suggests an intuitively appealing result that higher income consumers tend to be less price sensitive. The parameter estimate that measures the variation of price sensitivity across consumers, which is located in the column labeled "Standard Deviations", is statistically significant, providing evidence that consumers are heterogeneous with respect to their sensitivity to price changes of coffee products.

Table 2.3 Demand Estimates

Variables	Standard Logit Model ($\mu_{ij} = 0$)		Random Coefficients Model ($\mu_{ij} \neq 0$)		
	(1) OLS	(2) 2SLS	(3) GMM		
	Mean Coef $(\alpha, \beta's)$	Mean Coef $(\alpha, \beta's)$	Mean Coef $(\alpha, \beta's)$	Standard Deviations (Σ)	Interactions with Income (Γ)
Price ($/fl oz)	-14.236***	-146.975***	-163.61***	-11.8986***	10.8184***
	(0.117)	(1.021)	(2.663)	(0.312)	(2.068)
Constant	-14.776***	-7.637***	-34.0554***	9.0402***	
	(0.337)	(0.470)	(0.870)	(1.795)	
Single-cup Brew	-0.709***	4.297***	4.0616***	-0.044	1.9357***
	(0.006)	(0.039)	(0.124)	(0.177)	(0.152)
Organic	-0.9696***	-0.510***	-0.4861***		
	(0.006)	(0.009)	(0.017)		
Deal_cnt	0.153***	0.015***	0.0051*		
	(0.0008)	(0.0016)	(0.003)		
Caffeine	0.613***	0.652***	0.6624***		
	(0.002)	(0.0031)	(0.006)		
Large	0.858***	0.450***	0.3757***		
	(0.003)	(0.005)	(0.012)		
Time Fixed Effects	Yes	Yes		Yes	
IRI Market Fixed Effects	Yes	Yes		Yes	
Store Fixed Effects	Yes	Yes		Yes	
Brand Fixed Effects	Yes	Yes		Yes	
R-sq	0.615				
Wu-Hausman (Chi-sq)		33392.1***			
Stock and Yogo Weak Instrument Test (F)		112.22***			
			GMM Objective	0.0329	
No. of Observations	1,394,455	1,394,455		1,394,455	

***p<0.01; **p<0.05; *p<0.1. Standard errors are in parentheses.

To assess how much consumers value their coffee consumption experience using the single-cup brewing technology relative to the traditional auto-drip brewing method, we focus on the parameter estimates for the dummy variable, *Single-cup Brew*. The mean coefficient estimate, 4.0616, is positive and significant at 1%, providing evidence that the average consumer obtains more utility from the coffee consumption experience that uses single-cup brewing technology compared to the coffee consumption experience that uses auto-drip brewing method. In other words, a cup of freshly brewed coffee using the single-cup brewing technology is associated with higher levels of consumer satisfaction relative to levels of satisfaction associated with coffee consumption using the traditional auto-drip brewed method of ground coffee.

The parameter estimate that measures variation across consumers of utility differences obtained from the single-cup brewing technology consumption experience relative to traditional auto-drip brewing method consumption experience, which is located in the column labeled "Standard Deviations", is not statistically significant, suggesting that taste heterogeneity for the brewing method product attribute is mostly explained by the included demographics.[58] We find evidence that an important driver of consumers' heterogeneity with respect to their preference for the single-cup brewing technology consumption experience relative to traditional auto-drip brewing method consumption experience is their level of income. In particular, the positive and statistically significant coefficient estimate for the interaction between the *Single-cup Brew* dummy variable and consumer income, 1.9357, suggests that higher income consumers have a greater gain of utility from the coffee consumption experience using single-cup brewing technology compared to the coffee consumption experience that uses auto-drip brewing method.

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[58] Nevo (2000a) provides detailed discussions about the interpretation of the estimates of the standard deviations for the random coefficients.

In other words, evidence from the demand estimation suggests that, relative to lower income consumers, higher income consumers obtain an even greater satisfaction from the single-cup brewing technology consumption experience compared to their satisfaction obtained from traditional auto-drip brewing method consumption experience. Perhaps this finding is in part due to higher income households being better able to afford more expensive single-serve coffee brewing systems, which often cost $100 to $200 compared with an average price of $35 for many auto-drip coffee makers.[59]

The structural demand model allows us to obtain estimates of consumers' willingness to pay (WTP) for various measured product attributes. For example, the average WTP for the coffee consumption experience which uses single-cup brewing technology is given by the mean of the 200 individuals' marginal utility coefficient estimates on dummy variable, *Single-cup Brew*, ($\widehat{\phi}_t$) divided by their respective marginal utility coefficient estimate on price ($\widehat{\alpha}_t$) across all markets. The resulting mean WTP estimate is ¢2.52 per equivalent fl oz,[60] indicating that a typical coffee drinker is willing to pay up to ¢2.52 extra per equivalent fl oz to consume brewed coffee from the single-cup brewing method and thereby avoid using the traditional auto-drip brewing method. This is equivalently saying a typical coffee drinker is willing to pay ¢25 extra per standard 10 fl oz cup of brewed coffee using the single-cup technology rather than the traditional auto-drip method. We now better contextualize this WTP estimate of ¢2.52 per equivalent fl oz for the single-cup brewing method attribute.

From the previously discussed summary statistics in Table 2.1, we saw that the mean price across traditional auto-drip brewed coffee products in our sample is ¢1.61 per equivalent fl oz,

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[59] http://time.com/money/3733586/k-cups-price-cost-comparison-coffee/

[60] We convert the dollar value to cents for illustration.

while the mean price across single-cup brewed coffee products in our sample is ¢6.40 per equivalent fl oz. In other words, in terms of price per equivalent fl oz, the data reveals that, on average, single-cup brewed coffee products are 3.98 times as expensive as traditional auto-drip brewed coffee products. However, not all of this price difference is attributable to the difference in consumers' valuation of the single-cup brewing technology consumption experience versus the traditional auto-drip brewing technology consumption experience since the products across the two sets of product types may differ along several non-price product attribute dimensions. As we reported above, relevant parameter estimates from our demand model reveal that consumers are willing to pay ¢2.52 extra per equivalent fl oz just for the single-cup brewing technology consumption experience instead of the traditional auto-drip brewing method consumption experience. Assuming all other product attributes are equivalent to the average of said attributes for traditional auto-drip brewing method products, our WTP estimate also implies that, on average, a coffee drinker is willing to pay a price per equivalent fl oz that is 2.57 times the average price per equivalent fl oz of traditional auto-drip brewed coffee products just to enjoy the attribute of single-cup brewing technology as part of the consumption experience instead of the attribute of traditional auto-drip brewing method.

To present a picture of the relationship between individual-specific income level and the estimates of their marginal willingness to pay for the single-cup brewing technology product attribute, we plot the 200 individuals' annual income (in $100,000) and their respective estimates of willingness to pay (in cents/fluid ounce) from two select markets. These plots are shown in Figure 2.3 and Figure 2.4. It is clear that higher (lower) income individuals are willing to pay more (less) to have brewed coffee made from the single-cup coffee machines instead of the traditional auto-drip coffee makers. Similar results are found in other markets.

Figure 2.3 Individual Income and WTP in Select Market 1

Figure 2.4 Individual Income and WTP in Select Market 2
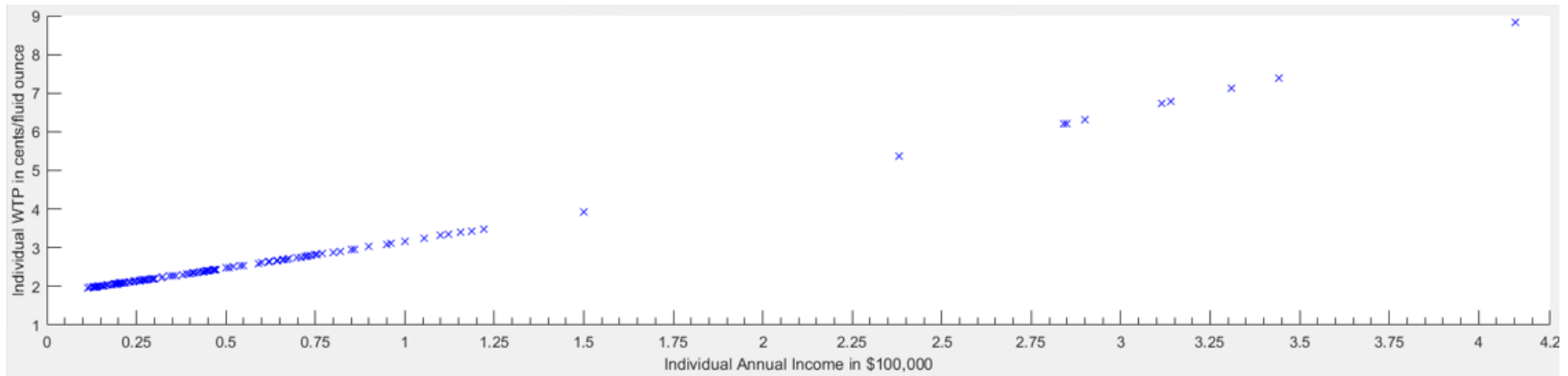
We now turn to discuss estimates for other product characteristics that affect consumer choice. For an average coffee drinker, organic coffee produces a negative marginal utility, suggesting that organic coffee products are less favorable than non-organic coffee during the sample period. This is an unexpected estimated demand impact of the organic attribute of coffee products. The other demand shifters all have expected demand impacts and are consistent with findings in previous studies. For example, the variable capturing the extent of promotional activities a product received during a month, *Deal_cnt*, has a positive and statistically significant coefficient estimate, suggesting that firms' promotional activities for a given coffee product serve to increase consumers' demand for the product. This finding is consistent with similar estimates in some previous work such as Guadadni and Little (1998), Gupta (1988), Lattin and Bucklin (1989), Grover and Srinivasan (1992), Boatwright, Dhar and Rossi (2004), Ansari, Bawa and Ghosh (1995). These studies all provide empirical evidence that promotional activities have a positive impact on coffee demand. Gupta (1988), for example, argues that promotion enhances a brand's value, which in turn enhances the probability of products of this brand being selected by consumers.

The coefficient estimate associated with the caffeine content variable is positive and statistically significant, suggesting that, holding all other coffee demand factors constant, consumers prefer coffee products that have higher caffeine content. A similar result is found in Bonnet and Villas-Boas (2016). The authors find consumers have significant and negative preference for caffeine-free products; thereby, a typical coffee drinker prefers coffee products that are not decaffeinated.

The coefficient estimate associated with the zero-one dummy package size variable, *Large*, is positive and statistically significant, suggesting that coffee products that are presented to

consumers in large packages (greater than 16 oz) have a higher demand relative to coffee products in smaller size packaging. This result is similar to findings in Guadagni and Little (1998) and Ansari, Bawa, and Ghosh (1995). Prendergast and Marr (1997) argue that larger packaged consumer goods normally reflect better value to average consumers, and consumers tend to choose larger packaged products as they are more likely to stand out on the shelf.

We use our demand model estimates to compute both own- and cross-price demand elasticities for products in the data sample. We then compute the mean of own-price demand elasticities at the coffee manufacturer level and report estimates of eleven select firms in Table 2.4. Mean cross-price demand elasticity estimates within and across the two coffee product types are reported in Table 2.5.

Own-price Elasticity of Demand Estimates

In Table 2.4, we report the average own-price elasticities for the eleven select coffee manufacturers broken down by coffee types. The last row in the table shows average own-price elasticities across all firms in the sample. Our demand model yields an average own-price elasticity of -4.57 across all products in the sample; an average own-price elasticity of -2.63 across all traditional auto-drip brewing method coffee products; and an average own-price elasticity of -9.69 across all single-cup brewing technology coffee products. The own-price elasticity estimate suggests that a 1% reduction in the price of a traditional auto-drip brew coffee product will, on average, result in a 2.63% increase in the quantity demanded for that product, while a 1% reduction in the price of a single-cup brew coffee product will, on average, result in a 9.69% increase in the quantity demanded for that product.

The own-price elasticity of traditional auto-drip brewing method coffee products in absolute magnitude, 2.63, is slightly smaller than analogous estimates obtained in previous studies: Krishnamurthi and Raj (1991) (own-price elasticity estimates ranging from 3.6 to 8.2); Broda and Weinstein (2006) (own-price elasticity estimate of 3.1); Foster, Haltiwanger and Syverson (2008) (own-price elasticity estimate of 3.65); Villas-Boas (2007b) (own-price elasticity estimates ranging from 5.6 to 6.8); and Nakamura and Zerom (2010) (own-price elasticity estimate of 3.96). We find Chintagunta et al. (2018) is the only work that provides an own-price elasticity estimate for single-cup brew coffee products in coffee markets in Portugal, with an estimate of 3.6 in absolute magnitude, which is smaller than our mean own-price elasticity estimate for single-cup brew coffee products in US markets.

The average own-price elasticity estimates reveal that consumer demand for single-cup coffee products is more sensitive to price changes of these products compared to the sensitivity of consumer demand for traditional auto-drip coffee products to price changes of these products. The difference in price sensitivity of consumer demand across these two coffee product types may in part be driven by consumers' broad perception of these two types of coffee products. Specifically, we previously discussed the result produced by our demand model suggesting that, relative to lower income consumers, higher income consumers have a greater preference for single-cup brewing technology coffee products compared to traditional auto-drip coffee products. This result further suggests that in classifying coffee products along a spectrum ranging from necessities to luxuries, single-cup brewing technology coffee products are likely to be closer to luxuries on the spectrum compared to traditional auto-drip coffee products. It is a well-established principle in microeconomics that luxury products tend to have higher elasticities of demand compared to necessity products. As such, where the two types of coffee products lie on the product

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classification spectrum ranging from necessities to luxuries in part may explain why single-cup brewing technology coffee products have a higher own-price elasticity of demand compared to traditional auto-drip brew coffee products.

Among the eleven coffee manufacturers, consumers are most price sensitive to products of KEURIG GREEN MOUNTAIN (with an estimate of -10.029) and least price sensitive to PRIVATE LABEL products (with an estimate of -2.618). Among traditional auto-drip brewing method coffee products, products of JOH A BENCKISER (JAB) have the most elastic demand (-3.952) while among single-cup brewing technology products, products of STARBUCKS COFFEE CO have the most elastic demand (-11.78).

Table 2.4 Break-down of Own-price Elasticities, by Coffee Type, Select Coffee Manufacturers with Share of Total Coffee $ Sales > 1% in 2012

		All Products		Auto-drip Brew Coffee Products		Single-cup Brew Coffee Products	
		Mean	Std. err.	Mean	Std. err.	Mean	Std. err.
Multi-coffee-type-product Firms	THE J M SMUCKER CO	-3.880	0.0050	-2.507	0.0018	-8.410	0.0098
	KEURIG GREEN MOUNTAIN	-10.029	0.0057	-3.811	0.0046	-10.700	0.0045
	KRAFT FOODS GROUP INC	-2.896	0.0057	-2.136	0.0019	-8.641	0.0277
	PRIVATE LABEL	-2.618	0.0044	-2.115	0.0024	-5.959	0.0160
	STARBUCKS COFFEE CO	-3.676	0.0047	-3.512	0.0022	-11.780	0.0471
	THE REILY COMPANIES	-2.666	0.0060	-2.582	0.0036	-10.232	0.0916
Single-coffee-type-product Firms	MASSIMO ZANETTI BEVERAGE USA			-1.939	0.0022		
	JOH A BENCKISER (JAB)			-3.952	0.0032		
	TATA TEA LTD			-2.508	0.0029		
	F GAVINA & SONS INC			-2.579	0.0042		
	TREEHOUSE FOODS INC					-7.620	0.0280
Mean Elasticities across all products in the sample		-4.570	0.0031	-2.626	0.0011	-9.692	0.0048

Table 2.5 Mean Cross-price Elasticities, by Coffee Type

i \ j	Single-cup Brew Coffee Products	Auto-drip Brew Coffee Products
Single-cup Brew Coffee Products	0.00118 (3.23e-06)	0.0007 (1.11e-06)
Auto-drip Brew Coffee Products	0.0005 (4.11e-07)	0.00085 (7.50e-07)

For cell entries i, j, where i indexes row and j column, given the percent change in market share of product i with a 1% change in price of product j. Each entry represents the mean of the elasticities from the 600 markets. Standard errors are in parentheses.

Cross-price Elasticity of Demand Estimates

Cross-price elasticity of demand estimates in Table 2.5 are relatively small in magnitude, but all estimates are positive and statistically different from zero, suggesting that consumers do perceive the coffee products in our sample as substitutable both within and across the two product types. It is also notable that the mean cross-elasticity estimates reveal the following intuitively appealing result: Coffee product pairs within any one of the two coffee product types, on average, have larger cross-elasticities (intra-product-type cross-elasticities) and therefore more substitutable compared to cross-elasticities among product pairs where products in the pair are in different product types (inter-product-type cross-elasticities), i.e., intra-product-type cross-elasticities are on average larger than inter-product-type cross-elasticities. Specifically, we see that among single-cup coffee products the mean cross-elasticity estimate is 0.00118, and among auto-drip coffee products the mean cross-elasticity estimate is 0.00085. These cross-elasticity estimates suggest that a 1% increase in the price of a single-cup coffee product, on average, results in a 0.00118% increase in the demand of another single-cup coffee product, while a 1% increase in the price of an auto-drip coffee product, on average, results in a 0.00085% increase in the demand of another auto-drip coffee product. However, mean cross-elasticity estimates between single-cup coffee products and auto-drip coffee products are 0.0007 and 0.0005, which are smaller in magnitude than the within product type mean cross-elasticity estimates. These mean cross-product type cross-elasticity estimates suggest that a 1% increase in the price of a single-cup coffee product, on average, results in a 0.0005% increase in the demand for an auto-drip product, while a 1% increase in the price of an auto-drip coffee product, on average, results in a 0.0007% increase in the demand for a single-cup product.

2.5.2 Markups and Marginal Costs

We report in Table 2.6 summary statistics of prices, price-cost margins, and marginal costs broken down by coffee types.[61] There is a total of 1,010,947 traditional auto-drip brewing method coffee products and 383,508 single-cup brewing technology coffee products in the sample. As previously reported in Table 2.1, and now again in Table 2.6, the average price per equivalent fluid ounce of single-cup brew coffee products is ¢6.4/fl oz, whereas the average price per equivalent fluid ounce of traditional auto-drip brew coffee products is only ¢1.6/ fl oz. The price difference suggests that, on average, it is more expensive for consumers to enjoy a cup of freshly brewed coffee using the single-cup brewing technology. In fact, using Keurig K-Cups to make brewed coffee may cost consumers up to 5 times more than brewing coffee from a pot using the traditional auto-drip method.[62]

Table 2.6 Summary Statistics of Price, Markup, and Marginal Cost, by Coffee Type

| | Traditional Auto-drip Brew Coffee Products | | | |
| | Price | Markup | | Marginal Cost |
Statistics	¢/fl oz	¢/ fl oz	% of Price	¢/fl oz
Mean	1.609	0.719	55.36	0.890
Median	1.509	0.692	46.87	0.792
10%	0.850	0.612	26.81	0.103
90%	2.461	0.850	87.96	1.761
Std. Dev.	0.673	0.137	285.79	0.706
No. of observations		1,010,947		

| | Single-cup Brew Coffee Products | | | |
| | Price | Markup | | Marginal Cost |
Statistics	¢/fl oz	¢/fl oz	% of Price	¢/fl oz
Mean	6.399	0.763	13.64	5.636
Median	6.573	0.711	11.23	5.827
10%	3.296	0.630	8.07	2.522
90%	8.316	0.920	23.49	7.608
Std. Dev.	1.911	0.217	14.82	1.935
No. of observations		383,508		

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[61] The model generates 3% of observations that have negative marginal cost estimate.

[62] https://www.businessinsider.com/keurig-cups-are-expensive-2015-3

Markups measured in cents per equivalent fluid ounce are positive for all products in the sample. A typical single-cup brew coffee product has a markup estimate of ¢0.76/fl oz, which is similar in magnitude to the average markup of a typical auto-drip brew coffee product of ¢0.72/fl oz. Consequently, with prices being very different across the two product types, the model predicts a considerably greater price-cost markup as a percent of price (price-cost margin or Lerner index) for a typical auto-drip coffee product, 55.4%, than that for a typical single-cup product, 13.6%. The table shows that only 10% of single-cup products have markups greater than 23.5%. The median price-cost margin among auto-drip coffee products in our data is 46.9%, which is close in magnitude to what others have found in the literature: Nakamura and Zerom (2010), 36.8%; Villas-Boas (2007b), 40.4%; and Bonnet and Villas-Boas (2016), 38.67%.

Finally, subtracting estimated markup from the observed price for each product yields implied marginal cost. Summary statistics on implied marginal cost estimates are reported in the last column of Table 2.6. Auto-drip brew coffee products are estimated to have mean marginal cost of ¢0.89/fl oz, whereas single-cup coffee products are estimated to have mean marginal cost of ¢5.6/fl oz, suggesting that single-cup pods production is more costly at the margin. Product-level marginal cost in the context of our analysis is the cost to the coffee manufacturer of producing the equivalent serving size in ounces of coffee grounds that makes one fluid ounce of brewed coffee. Single-cup coffee products are individually portion-packed ground coffee pods packed in either bags or cans; whereas traditional auto-drip brew coffee products are simply ground coffee packed in bulk either in bags or cans. This difference in how ground coffee is packaged across these two coffee product types may in part explain the difference in marginal costs across the product types.

2.6 Counterfactual Analysis

Using the estimated product-level marginal costs, estimated structural parameters, and first-order condition equations resulting from Nash price-setting behavior of firms, we simulate the resulting market equilibrium from imposing the counterfactual assumption that consumers are indifferent between coffee consumption that uses single-cup brewing technology and coffee consumption that uses traditional auto-drip brewing method. Imposing the counterfactual assumption that consumers are indifferent between the two types of brewing methods is achieved by setting to zero coefficient estimates associated dummy variable, *Single-cup Brew*, in the utility function, i.e., based on demand parameter estimates reported in Table 2.3, we would set 4.0616, -0.044 and 1.9357 to 0. The counterfactual experiment is performed to investigate how equilibrium market outcomes of interests (prices, consumer demand, firm profits and consumer welfare) are predicted to change if consumers equally value the single-cup brewing technology coffee consumption experience and the traditional auto-drip brewing method consumption experience.

The new equilibrium price vector, p^*, is obtained by numerically searching for the vector of prices that satisfy the following equation:

$$p^* = \widehat{mc} - [\Omega * \Delta(p^*)]^{-1} s(p^*) \tag{2.10}$$

where $\widehat{mc}$ is the vector of recovered product-level marginal cost estimates based on all demand parameter estimates in Table 2.3. However, the demand parameter estimates used for constructing matrix $\Delta(p^*)$ and vector $s(p^*)$ are the estimates in Table 2.3, with the exception that all coefficient estimates associated with the dummy variable, *Single-cup Brew*, in the utility function are set equal to zero. A comparison of the actual observed price vector p from the data with the model predicted new equilibrium price vector p^* reveals how equilibrium price would be

affected if consumers' preference for the single-cup brewing technology coffee consumption experience were to be removed.

We next discuss how the new equilibrium price vector $\boldsymbol{p}^*$ is used to recover other equilibrium market outcomes of interest. The discussion begins with predicted changes in coffee demand and firm variable profits, and then turn to the analysis of predicted changes in equilibrium product prices and markups. We leave for last, discussing predicted changes in consumer welfare.

2.6.1 Predicted Changes in Coffee Demand, Markup, and Variable Profits

We use the following equations to compute counterfactual coffee demand and manufacturers' variable profits respectively:

$$\boldsymbol{q}^* = M \times \boldsymbol{s}(\boldsymbol{p}^*; \hat{\beta}, \hat{\phi} = 0, \hat{\alpha}, \hat{\Gamma}, \hat{\Sigma}) \tag{2.11}$$

$$\widehat{VP}_f^* = \sum_{j \in F_f} (p_j^* - \widehat{mc}_j) \times q_j^* \tag{2.12}$$

where $\boldsymbol{q}^*$ is a vector of counterfactual product demand levels measured in equivalent fluid ounces; and $\boldsymbol{p}^*$ is the previously obtained vector of counterfactual equilibrium prices predicted by the model. A comparison of the actual demand $\boldsymbol{q}$ with the counterfactual demand $\boldsymbol{q}^*$ reveals how much consumer coffee demand would be affected assuming coffee drinkers are indifferent between the two brewing methods. $\widehat{VP}_f^*$ represents manufacturer f's counterfactual variable profit. For each individual product, variable profit is computed by multiplying the counterfactual product markup $(p_j^* - \widehat{mc})$ and counterfactual product demand q_j^*. $\widehat{VP}_f^*$ is the sum of variable profits across the menu of products of firm f in a given market. We compare factual and counterfactual variable profits to evaluate changes in profitability at the product level as well as at the manufacturers' level. The above variable profit function implies that firm f's variable profit depends both on its product markups and demand levels. Therefore, we are able to decompose

changes in variable profits by changes in markups and demand levels, and examine how these components drive the changes in variable profits.

In Table 2.7, we summarize changes in monthly market demand, markup and variable profit for traditional auto-drip brew coffee products as well as single-cup brew coffee products. Among traditional auto-drip brew coffee products in a market, we find predicted increases in consumer demand, with a mean predicted increase of 3.88%. In contrast, consumer demand for single-cup coffee products in a market is predicted to decline by a mean 98.5%.[63] Consistent with intuition, almost all auto-drip coffee products in the data are predicted to have a positive change in demand, whereas each single-cup coffee product is predicted to have a negative change in demand.

In terms of predicted changes in product markups, we find that across markets, a subset of auto-drip brew coffee products would experience increases in markup, with increases as high as 52%, while the remainder of auto-drip products would experience decreases in markup, with decreases as low as 5%. The predicted mean change in markup for auto-drip products is positive and equal to 0.55%. Similarly, a subset of single-cup brew products are predicted to experience increases in markup, with increases as high as 51%, while the remainder of single-cup products are predicted to experience deceases in markup, with decreases as low as 67%. The predicted mean change in markup for single-cup products is negative, i.e., there is a mean decline (5.8%) in

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[63] We summarize the quantity change for all auto-drip brew ground coffee products and all single-cup brew coffee products in the whole data sample before and after the simulation. We find 99.2% auto-drip brew ground coffee products have an increase in demand with the min of 0.00009% and the max of 73%, only 0.8% has demand reduced in the counterfactual. All single-cup brew coffee products experience reduction in demand in the simulation. At the market level, the model predicts a mean increase in auto-drip brew coffee demand in 599 out of total 600 markets. We believe the model predicts quite well the change in product demand for both coffee types, even though a few auto-drip brew coffee products have negative counterfactual demand changes.

markups of single-cup products. On average, the predicted changes in markups are small in magnitude relative to the predicted changes in product demand levels. As such, the predicted change in variable profit for each coffee product is often predominantly driven by the change in the product's demand rather than the change in its markup.

Auto-drip brew coffee products in a market show a mean predicted increase in variable profit of 4.6%, with increases as high as 117%. However, single-cup brew coffee products are predicted to experience reductions in variable profits, with a mean reduction of 98.6%. The predicted changes in auto-drip brew coffee products' demand levels and variable profits suggest significant cannibalizing effects associated with the introduction and growing presence of single-cup brew technology coffee products. Put differently, suppose consumers no longer have a preference for the single-cup brew coffee consumption experience, a typical auto-drip brew coffee product could have had much greater demand and profitability in such a counterfactual world. The counterfactual removal of consumers' preference for the single-cup brew technology also implies a substantial decline in profitability of a typical single-cup brew coffee product.

2.6.2 Predicted Changes in Prices and Markups

Results in Table 2.7 reveal that counterfactual removal of consumer preference for the single-cup brewing technology may have a positive or negative impact on the markup of any coffee product. Predicted changes in product markups underlie counterfactual impacts on equilibrium price levels based on the assumption that product-level marginal costs are unchanged. In what follows, we discuss how the introduction and growing presence of the single-cup brew coffee products affect market equilibrium price levels.

Before we examine the counterfactual change in equilibrium prices, it is useful to discuss the potential forces at play in the market equilibrium analysis. Put differently, should we expect equilibrium prices of auto-drip brew coffee products to rise, decline or remain unchanged, and what should we expect about equilibrium price changes for single-cup brew coffee products?

The counterfactual exercise causes shifts in product demands. In particular, by imposing the preference change that the preferred single-cup brew consumption experience becomes equally satisfying to the auto-drip brew consumption experience, the model predicts a reduction in demand for single-cup brew coffee products, but a rise in demand for auto-drip brew coffee products. The increase in demand for auto-drip brew coffee products will put an upward pressure on prices of these products owing to a direct demand effect. Higher prices for auto-drip brew coffee products will in turn put upward pressure on prices of single-cup brew coffee products owing to strategic Nash equilibrium price-setting behavior of firms. In other words, the increase in demand for auto-drip coffee products puts upward pressure on prices of both types of coffee products. In contrast, the decrease in demand for single-cup brew coffee products will put a downward pressure on prices of these products owing to a direct demand effect. Lower prices for single-cup brew coffee products will in turn put downward pressure on prices of auto-drip brew coffee products owing to strategic Nash equilibrium price-setting behavior of firms. In other words, the decrease in demand for single-cup brew coffee products puts downward pressure on prices of both types of coffee products. In summary, everything else being unchanged, the simultaneous increase in demand for auto-drip brew coffee products but decrease in demand for single-cup brew coffee products can result in equilibrium prices of both product types to either rise or fall.

Table 2.7 Summary Statistics of Counterfactual Changes in Demand, Markup, and Variable Profit for Coffee Products in a Market

		Auto-drip Brew Coffee Products				Single-cup Brew Coffee Products			
		Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Demand	Market Mean Initial Levels (fl oz)	15410	5865.99	6936.63	36622.69	2219.29	1182.89	444.4	6536.91
	Market Mean Counterfactual Levels (fl oz)	15977	6143.04	7116.89	39255.29	31.48	26.7813	0.0001	167.33
	Change (fl oz)	567.33	496.62	-659.23	3096.93	-2187.81	1168.83	-6419.36	-438.17
	% Change (%)	3.88	2.84	-3.33	31.22	-98.54	0.92	-99.99	-96.36
Markup	Market Mean Initial Levels (¢/fl oz)	0. 73	0.07	0.61	1.70	0.76	0.15	0.61	2.82
	Market Mean Counterfactual Levels (¢/fl oz)	0. 74	0.07	0. 61	1.46	0.71	0.07	0. 59	1.51
	Change (¢/fl oz)	0. 0039	0.04	-0.57	0.59	-0.05	0.13	-2.11	0.63
	% Change (%)	0.55	2.36	-5.15	52.31	-5.81	8.58	-66.96	51.09
Variable Profit (monthly)	Market Mean Initial Levels ($)	122.42	54.90	50.74	422.2	17.51	12.21	2.96	163.38
	Market Mean Counterfactual Levels ($)	127.86	57.82	51.94	431.32	0.22	0.18	1.02e-06	1.13
	Change ($)	5.44	9.50	-110.55	129.65	-17.29	12.16	-163.38	-2.92
	% Change (%)	4.59	6.07	-7.98	117.69	-98.57	0.93	-99.99	-95.68

In Table 2.8, we show the summary results of the counterfactual changes in prices of auto-drip brew coffee products and single-cup brew coffee products. The mean counterfactual change in prices of auto-drip brew coffee products is positive and the mean counterfactual change in prices of single-cup brew coffee products is negative, even though some products of either coffee type have both positive and negative counterfactual price changes. In particular, under the counterfactual scenario in which the preferred single-cup brew consumption experience becomes equally satisfying to the auto-drip brew consumption experience, our model predicts that, on average, prices of auto-drip brew coffee products will rise by 0.4%, even though prices of a subset of these products will fall, with declines as large as 17.6%, and prices of the remainder of these products will rise, with increases as large as 116%. Similarly, the counterfactual change in consumers' preference for coffee brewing technology also predicts that, on average, prices of single-cup brew coffee products will fall by 0.02%, even though prices of some of these products will rise, with increases as large as 68%, and prices of some of these products will fall, with declines as large as 11%. In summary, since counterfactual removal of consumers' preference for the single-cup brew consumption experience is predicted to increase auto-drip brew coffee product prices on average, then we can reasonably infer that the introduction of the consumer-preferred single-cup brewing technology resulted in auto-drip brew coffee product prices being lower, on average, than would otherwise be the case.

Table 2.8 Summary Statistics of Counterfactual Change in Prices, by Coffee Type

	Auto-drip Brew Coffee Products				Single-cup Brew Coffee Products			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Market Mean Initial Levels (¢/fl oz)	1.593	0.109	1.310	1.947	6.410	0.317	5.352	7.620
Market Mean Counterfactual Levels (¢/fl oz)	1.598	0.133	1.285	3.426	6.410	0.487	5.351	11.032
Change (¢/fl oz)	0.005	0.071	-0.217	1.698	-0.0006	0.384	-0.636	4.834
% Change (%)	0.368	4.875	-17.6	116.31	-0.019	5.658	-10.6	67.7

2.6.3 Welfare Analysis

The estimated random coefficients logit demand model permits us to analyze the change in welfare associated with imposing the counterfactual assumption that consumers are indifferent between coffee consumption that uses single-cup brewing technology and coffee consumption that uses traditional auto-drip brewing method. Following Nevo (2001), McFadden (1984), Small and Rosen (1981), Petrin (2002), Train (2009), and many others, the consumer surplus for consumer i is given by:

$$CS_i = \frac{\ln\left(\sum_{j=0}^{J} e^{V_{ij}}\right)}{\alpha_i} \tag{2.13}$$

where α_i is the random coefficient for price and $V_{ij} = \delta_j + \mu_{ij}$. The change in consumer surplus due to the counterfactual change in consumer preference for the coffee type is given by:

$$\Delta CS_i = \frac{\ln\left(\sum_{j=0}^{J} e^{V_{ij}^*}\right) - \ln\left(\sum_{j=0}^{J} e^{V_{ij}}\right)}{\alpha_i} \tag{2.14}$$

where V_{ij}^* is evaluated at the new counterfactual equilibrium price vector p^* and when the coefficient estimates associated with the *Single-cup Brew* dummy variable are set to zero, while V_{ij} is evaluated at actual price vector, p, and the coefficient estimates reported in Table 2.3.

Table 2.9 presents summary statistics of the average consumer surplus obtained from consuming one fluid ounce of brewed coffee by a typical coffee drinker in a sample of 200 individuals in each market from the Public Use Microdata Sample (PUMS) data. As the price of a product is measured by dollar(s) per fluid ounce, an individual's consumer surplus measure is interpreted as their net benefit in dollar amount from consuming one fluid ounce of brewed coffee. We convert the dollar(s) to cent(s) in the table. In Table 2.9, a typical consumer in a market is predicted to have a mean decrease in welfare of 2%. In other words, if consumers' preference for the single-cup brew technology is counterfactually removed, then a typical coffee drinker's net benefit from consuming one fluid ounce of brewed coffee is predicted to decrease by 2%. This result, in turn, suggests that the introduction of the consumer-preferred single-cup brewing technology resulted in an increase in consumer surplus.

Table 2.9 Summary Statistics of Counterfactual Change in Individual Consumer Surplus in a Market

		Mean	Std. err.	Min	Max
Consumer Surplus for a typical individual ($\widehat{CS}_i$)	Initial Levels (¢/fl oz)	0.056	0.004	0.002	1.230
	Counterfactual Levels (¢/fl oz)	0.055	0.004	0.002	1.223
	Change (¢/fl oz)	-0.001	0.00005	-0.012	0.008
	% Change (%)	-2.013	0.093	-9.619	28.078

2.7 Conclusion

The introduction of the single-cup brewing technology in the late 2000s has not only changed the way many brew-at-home coffee drinkers brew and consume coffee in daily life, a change from brewing one "pot" at a time to making one cup at a time, but also altered the overall landscape of the US brew-at-home coffee market. This paper is motivated by the fact that sales of coffee products that require the single-cup brewing technology rose quickly, while sales of coffee

products that use the traditional auto-drip brewing method were substantially cannibalized with the introduction and growing presence of the single-cup brewing technology. To the best of our knowledge, this paper constitutes the first formal study of the economic effects of the introduction and growing presence of the single-cup brewing technology on the US brew-at-home coffee market.

The empirical analysis is conducted using IRI retail-level scanner data on sales of coffee products during year 2012. We find consumers, on average, prefer consuming brewed coffee products using the single-cup brewing method instead of the traditional auto-drip brewing method. In particular, a typical coffee drinker is willing to pay up to ¢2.52 extra per equivalent fluid ounce to consume brewed coffee using the single-cup brewing technology instead of using the traditional auto-drip brewing method. This relative gap in consumers' willingness to pay for the two distinct coffee brewing method technologies increases with consumer income, that is, higher income consumers obtain an even greater satisfaction from coffee consumption with the single-cup brewing technology.

To investigate the market effects associated with the presence of single-cup brewing technology on the US brew-at-coffee market, we use the estimated model to perform a counterfactual experiment. The counterfactual experiment involves removing consumers' relative preference for using the single-cup brewing technology instead of the traditional auto-drip brewing method, and simulating new equilibrium market outcomes based on consumers' counterfactual preferences. The counterfactual preference change yields a mean increase in consumer demand for traditional auto-drip brew coffee products of 3.88%, and a substantial mean decrease in demand for single-cup brew coffee products of 98.5%. Second, auto-drip brew coffee products are predicted to have a mean increase in variable profit of 4.6%, with increases as high as 117%,

suggesting, at least in some markets, there exist substantial cannibalizing effects associated with the introduction and growing presence of single-cup brewing technology coffee products on traditional auto-drip brew coffee products. Third, the counterfactual experiment also predicts a mean increase in prices of auto-drip brew coffee products and a mean decrease in prices of single-cup brew coffee products, suggesting that the introduction of the consumer-preferred single-cup brewing technology resulted in auto-drip coffee product prices being lower, on average, than would otherwise be the case.

Last, the consumer welfare analysis suggests that consumers enjoy net benefits from the presence of single-cup coffee brew technology. The introduction and growing presence of single-cup brewing technology is predicted to increase a typical coffee drinker's welfare by 2%.

It is worth pointing out some limitations of our analysis. We simplify modeling the supply side of the market by assuming retailers play a passive role in the price-setting game. Other vertical relationships between coffee manufacturers and retailers can be examined as a potential extension of this current work [see Villas-Boas (2007b) and Hellerstein and Villas-Boas (2010)]. It may be interesting to investigate whether or not various vertical contracts between manufacturers and retailers influence predicted changes in market outcomes given the counterfactual change in consumer preference we consider.

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Appendix A - Proof of Lemma 1 for Chapter 1

Assume positive price and quantity for each firm, we first compute the Nash equilibrium

quantity by substituting the equilibrium price into demand function, which gives:

$$q_i^* = \frac{\beta}{2\beta - (n-1)\tilde{\beta}} H - \frac{\beta(\beta + \tilde{\beta})}{2\beta + \tilde{\beta}} c_i + \frac{\beta^2 \tilde{\beta}}{(2\beta + \tilde{\beta})[2\beta - (n-1)\tilde{\beta}]} \left(\sum_{j=1}^{n} c_j \right)$$

$$= \frac{(2\beta + \tilde{\beta})H - (\beta + \tilde{\beta})[2\beta - (n-1)\tilde{\beta}]c_i + \beta\tilde{\beta}\left(\sum_{j=1}^{n} c_j \right)}{2\beta - (n-1)\tilde{\beta}} \left(\frac{\beta}{2\beta + \tilde{\beta}} \right)$$

The sufficient and necessary conditions for the strictly positive price and quantity requires

the following simultaneous inequalities hold:

$$
\begin{cases}
P_i^* > 0 \\
q_i^* > 0 \\
c_i > 0 \\
H > 0 \\
\beta > \tilde{\beta} > 0
\end{cases}
\equiv
\begin{cases}
\frac{(2\beta + \tilde{\beta})H + \beta[2\beta - (n-1)\tilde{\beta}]c_i + \tilde{\beta}\beta \sum_{j=1}^{n} c_j}{2\beta - (n-1)\tilde{\beta}} \left(\frac{1}{2\beta + \tilde{\beta}} \right) > 0 \\
\frac{(2\beta + \tilde{\beta})H - (\beta + \tilde{\beta})[2\beta - (n-1)\tilde{\beta}]c_i + \beta\tilde{\beta} \sum_{j=1}^{n} c_j}{2\beta - (n-1)\tilde{\beta}} \left(\frac{\beta}{2\beta + \tilde{\beta}} \right) > 0 \\
c_i > 0 \\
H > 0 \\
\beta > \tilde{\beta} > 0
\end{cases}
$$

The right-hand side system of inequalities suggests the following two scenarios:

$$
(1)
\begin{cases}
2\beta - (n-1)\tilde{\beta} > 0 \\
(2\beta + \tilde{\beta})H + \beta[2\beta - (n-1)\tilde{\beta}]c_i + \beta\tilde{\beta} \sum_{j=1}^{n} c_j > 0 \\
(2\beta + \tilde{\beta})H - (\beta + \tilde{\beta})[2\beta - (n-1)\tilde{\beta}]c_i + \beta\tilde{\beta} \sum_{j=1}^{n} c_j > 0 \\
c_i > 0 \\
H > 0 \\
\beta > \tilde{\beta} > 0
\end{cases}
$$

Or

$$
(2)
\begin{cases}
2\beta - (n-1)\tilde{\beta} < 0 \\
(2\beta + \tilde{\beta})H + \beta[2\beta - (n-1)\tilde{\beta}]c_i + \beta\tilde{\beta} \sum_{j=1}^{n} c_j < 0 \\
(2\beta + \tilde{\beta})H - (\beta + \tilde{\beta})[2\beta - (n-1)\tilde{\beta}]c_i + \beta\tilde{\beta} \sum_{j=1}^{n} c_j < 0 \\
c_i > 0 \\
H > 0 \\
\beta > \tilde{\beta} > 0
\end{cases}
$$

The set (2) conditions have a contradiction, as $H > 0$, $\beta > 0$, marginal costs c_i are non-negative. If $2\beta - (n-1)\tilde{\beta} < 0$, this contradicts with $(2\beta + \tilde{\beta})H - (\beta + \tilde{\beta})[2\beta - (n-1)\tilde{\beta}]c_i + \beta\tilde{\beta}\sum_{j=1}^{n} c_j < 0$. Therefore, we conclude that to have positive Nash price and quantity requires the following conditions (necessary conditions) hold:

$$\begin{cases} 2\beta - (n-1)\tilde{\beta} > 0 \\ (2\beta + \tilde{\beta})H + \beta[2\beta - (n-1)\tilde{\beta}]c_i + \beta\tilde{\beta}\sum_{j=1}^{n} c_j > 0 \\ (2\beta + \tilde{\beta})H - (\beta + \tilde{\beta})[2\beta - (n-1)\tilde{\beta}]c_i + \beta\tilde{\beta}\sum_{j=1}^{n} c_j > 0 \\ c_i > 0 \\ H > 0 \\ \beta > \tilde{\beta} > 0 \end{cases}$$